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Radio Frequency Toolbox for Drone Detection and Classification

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Abstract:

The research aims to detection and classification drone, using radio Frequency Toolbox. In order try to evaluate and test the detection capability of the module RF-class toolbox, we decided to carry out distance analysis test to determine how far away the drone can be from the detection module and its presence not to being detectable even when it is transmitting. For this test, the Distance between the drone and the detection module was varied and detection data was collected. For the first test of supervised training. Data were collected for 200 samples of when the phantom drone was ON and 200 samples of when Mavic was ON. Both samples were labeled to create the class for classification purposes. The total sample used for the training data is 400 in total.

We decided to start with smaller training samples and later increase the number of samples used for training. For the second test, the total sample used for the training is 3000 in total; 1500 for when Mavic is turned on and another 1500 for when phantom is turned on.

From the experiment and results shown so far, we can successfully classify signals that are being transmitted from DJI phantom and Mavic drones. Using the machine learning training and testing we observed that out of the different classification algorithms, KNN works best and provide the highest accuracy.

Keywords: Radio Frequency, Toolbox, Drone Detection, Drone Classification, Embedded Sensors

Introduction:

Unmanned aerial vehicle. The First question a person not familiar with the term will ask is what is a UAS? In literature and in general, the entire operating equipment, which is comprised of an aircraft, the control station, and the wireless link between the aircraft and its control system, is described as the UAS. The terms UAS and UAV can be interchangeable in their usages in this thesis but can be regarded to mean the same thing.

Drone seems like the more used term among hobbyists and is an unmanned or autonomous aircraft, which is commonly used, in a military context while it is also used to designate any of the numerous available classification or types of aerial unmanned vehicle in the common language. It is now easier for civilians to own drones as the cost falls. As we, all know drones have a variety of important applications and can also be used for negative effects too.

Detection of drone signals presents an interesting challenge to researchers and hobbyists in general. Drones can operate and appear in all directions so therefore a detection and monitoring equipment should also be able to monitor multiple directions at the same time. It is difficult to effectively distinguish the drone appearance from that of other ying objects such as kites, birds etc. most especially in a case where the drone is far from the detection module As an electronic device which still relies on power to work it presents a limitation to its battery and communication and as a result consumer-grade drown essentially operates a very low altitude. objects and environment present an obstruction to the drone usage often.

Drones Detection Methods

In literature, there exist different methods of drone detection, some notable detection methods are audio, video, thermal, radar and radio frequency detection. Discusses some of the challenges faced in drone detection and presented an approach to detection using an audio assisted array. Implemented a passive radar technique approach to detection of drone signal. Discussed some principles of drone detection using the radio frequency approach. In a thermal approach to drone detection was investigated

There are many methods for detections drones such as:

- Audio Detection
- Video Detection
- Thermal detection
- Radar detection
- Radar frequency detection

How Drone Works

The drone is made of two fundamental parts, which are the remote control and the aircraft. Both communicate with one another using a radio frequency communication link. The Figure below presents the architecture and architectural design and components of most drones (Bilal et al., 2019).

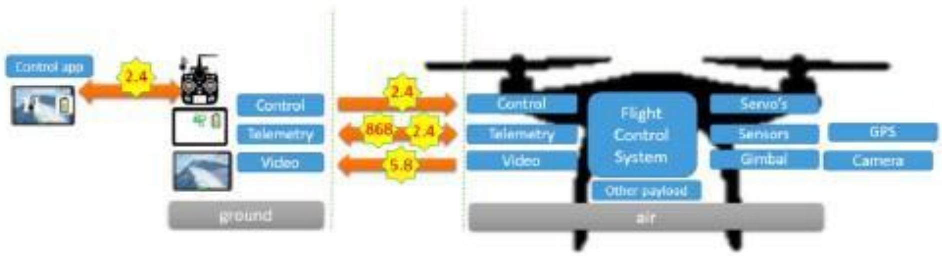


Figure 1: The Components of the Drones

There are other available detection techniques available in literature and in practice, but we have chosen to use energy detection because of its simplicity, as it does not employ a lot of computational complexity. This processing involves the labeling and training of the collected features. GNU radio blocks will be used to implement the detection, extraction, classification and testing.

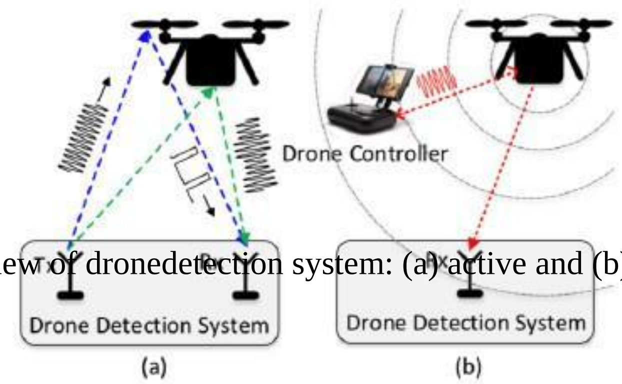


Figure 2: The overview of dronedetection system: (a) active and (b) passive approaches

Literature Review:

In literature and research, articles there exist some different detection methods. The detection method should be able to overcome many obstacles that could make the detection di cult. Among the existing detection methods that have been implemented so far, not all of them are independent from these factors so they cannot be efficacious. Some of the factors are that may affect detection are:

1. The typical low signal to noise ratio (SNR) in the transmissions.
2. Multi-path and fading in wireless communications.
3. The instable noise level in the channel.
4. The need for a low sensing time (Kaleem & Rehmani, 2019).

It has been identified that the best way to detect signals with maximum SNR is to use a matched filter receiver. Its most important characteristics is the low execution time, but the signal properties to be detected is known before the process begins. This method includes the demodulation of the signal which means that the receiver should agree with the source, estimate the channel conditions and to know the signal nature. This method is mostly useful for dedicated receivers like in TV transmissions (Kaleem et al., 2019).

Most signals have statistical properties that vary periodically with time, which are called cyclostationary features. Hence, more accurate detection can be achieved by exploiting the inherent periodicity of the autocorrelation function of the signals. Modulated signals have a SCF with specific and unique characteristics so, comparing them with a database containing list of typical features, the signal detection is possible. The limitations of this method are that it needs a great computational complexity and also the knowledge of some signal parameters of the signal under test like the carrier frequency (Derek, 2019).

Methodology:

Detecting the Drone Signal

Energy detection will be implemented and demonstrated using software dened radio. This will be achieved using two computers with GNU radio companion software installed and two HackRf hardware for transmit and receive (Edwin et al., 2017).

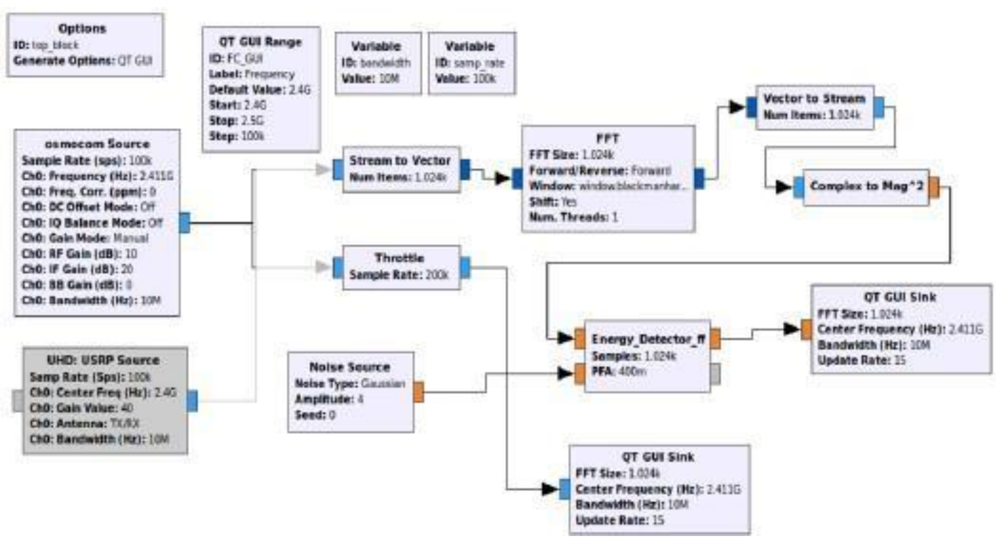


Figure 3: Flow graph of Energy Detector on GNU radio

Orthogonal Frequency Division Multiplexing

Orthogonal Frequency Division Multiplexing is a basic building block for many of the current modulation schemes including; 802.11 WLAN, 802.16 WiMAX, and 3GPP LTE. Orthogonal Frequency Division Multiplexing is a digital multi-carrier modulation scheme that uses multiple subcarriers within the same single channel. It makes use of a large number of closely spaced orthogonal subcarriers that are transmitted in parallel. The subcarriers are orthogonal to each other, and A guard interval is added to each symbol to minimize the channel delay spread and inter symbol interference (Mendis & Jin, 2017).

Figure shown below; one will get a better understanding of the main concepts of an OFDM signal and the inter-relationship between the frequency and time domains. In the frequency domain, many adjacent subcarriers or tones are each independently modulated with complex data. Then an Inverse FFT transform is performed on the frequency-domain subcarriers so as to produce the OFDM symbol in the time-domain. After which in the time domain, guard intervals are inserted between each of the symbols to prevent inter-symbol interference at the receiver which is caused by multi-path delay spread in the radio channel.

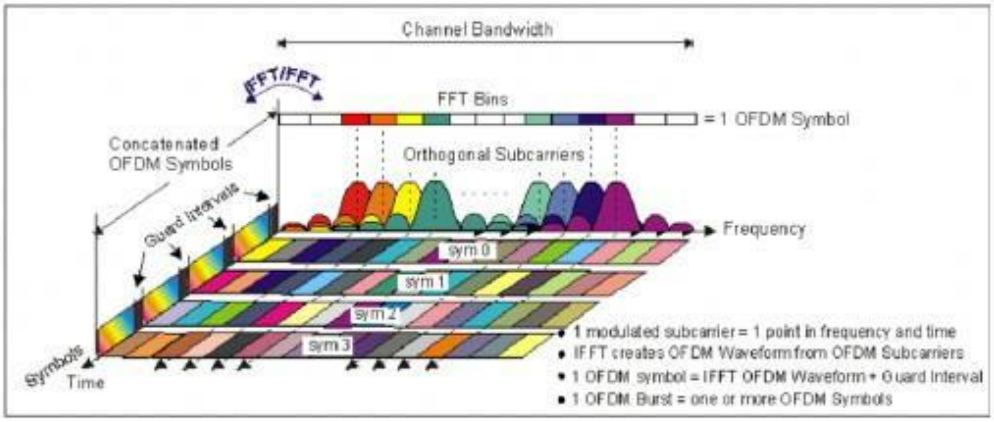


Figure 4: Representation of OFDM Signal

Machine Learning Classification

What is machine learning? There are different definitions but generally, it is a branch of artificial intelligence that is concerned with the design and development of algorithms that allow computers to evolve behaviors based on empirical data. The idea is for machines are able to learn and make predictions without explicitly being programmed. As intelligence requires knowledge, it is necessary for the computers (Yapici, et al., 2019).

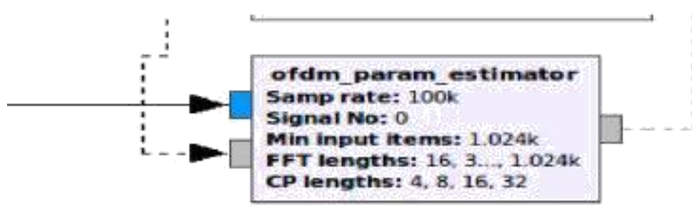


Figure 5: OFDM estimator in GNU Radio

To acquire knowledge. We incorporated a machine-learning block to our work by developing a custom machine learning testing block on GNU Radio

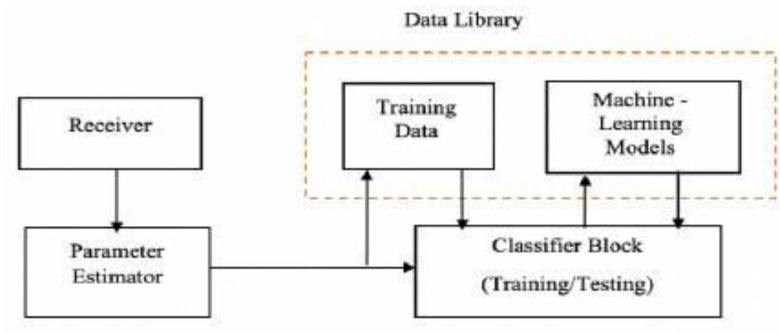


Figure 6: Breakdown of the machine-learning module

Decision Tree

A decision tree has a owchart-like structure in which each of its internal node represents a test on an attribute for example in a coin toss scenario, whether a coin ip comes up heads or tails, each of the branch represents the outcome of the test, and each leaf node represents a class label which is the decision taken after computing all attributes. The paths represented from the root to leaves denotes the classification rules. Typically, a decision tree algorithm consists of three types of nodes:

1. Decision nodes - this are usually represented by squares
2. Chance nodes - usually represented by circles
3. End nodes usually represented by triangles (Victor et al., 2017)

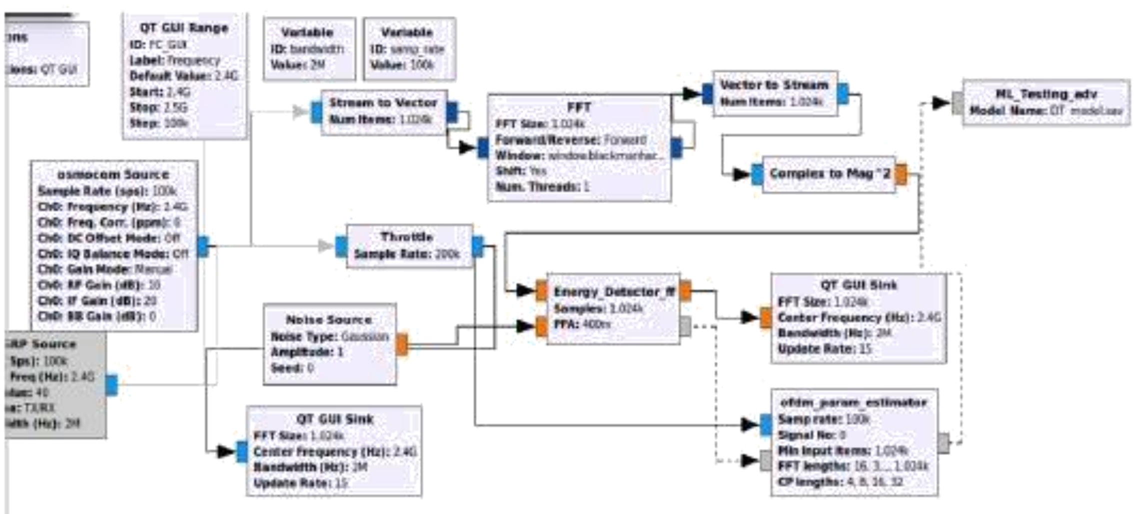
Experiments and Results

Setup and Testing

In this chapter, the detection and classification module using GNU radio companion will be discussed. For our experiment, a customized machine learning testing block, energy detection and parameter estimation block were developed to detect and classify drone signals using gnu radio companion and hackRF hardware. The RF signal raw data will be collected after implementing and connecting all the blocks. In order to carry out the experiment and collect data from the detection module, it is necessary to be able to ascertain and know for sure the drone transmit frequency.

We collected data for different scenarios that will be used as the base of our classification. First instance is when the phantom drone is turned ON and is the only signal being transmitted; (Degen et al., 2017).

The second instance is when the Mavic drone is ON and also is the only signal being transmitted. This makes it easier for us to tune and monitor the GNU radio companion frequency spectrum during testing. In order to collect data from the detection block, we need to be able to transmit at a specific frequency, monitor and collect data for training, and then test the classification using the custom machine learning testing block. For this experiment, the drone is transmitting on channel 13 and the receiver module on GNU radio is centered at 2.411Ghz



How It Works

Dataset for the two scenarios was collected for over 10 minutes at different conditions so as to have varying instances for each scenario. These collected data were used for machine learning training to build a class. The Testing block uses data trained based on support vector machine model of machine learning training to make predictions. The features used for the classification are signal power, decision/threshold for detection (energy detection) and OFDM parameter (subcarrier space, symbol time, fft length, cp length). Using different machine-learning model to train the features we expect the decision model to predict Mavic when signal transmitted is from Mavic and phantom the signal is from the phantom drone in real time

Figure 7: GNU Radio Flow graph for detection and classification.

Machine Learning Data Training and Testing Case 1

For our experiment we will be using the supervised method of machine learning classification to train the models which will be used for detection and classification, and the data used for classification will be labeled accordingly. The training data contains parameters which will be used for classification, and same amount of data for each object to be classified is collected. For the first test of supervised training. Data were collected for 200 samples of when the phantom drone was ON and 200 samples of when Mavic was ON. Both samples were labeled to create the class for classification purposes. The total sample used for the training data is 400 in total.

We decided to start with smaller training samples and later increase the number of samples used for training. For the second test, the total sample used for the training is 3000 in total; 1500 for when Mavic is turned ON and another 1500 for when phantom is turned ON.

Case 1 Testing and Result

Based on the data used for training and testing below is the performance classification metric in Python after the training data was split into training and testing for validation. figure below shows the chart consisting of the performance metric generated in Python using the KNN classifiers for training the data samples. We decided to use KNN after performing an accuracy comparison among different classifiers like decision tree, linear regression and support vector machine.

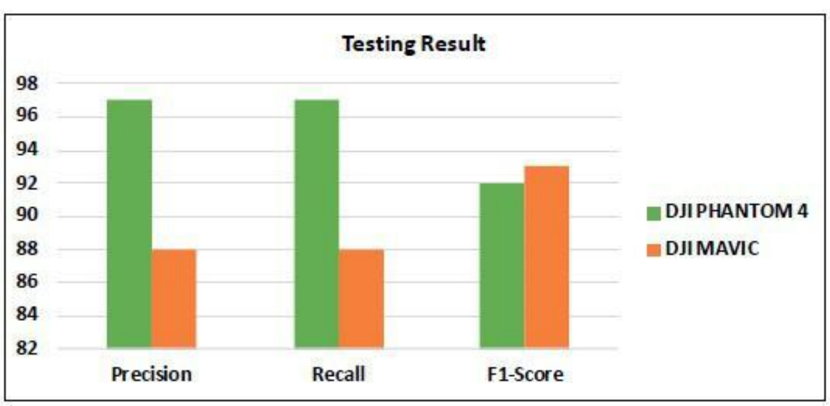


Figure 8: Experimental Setup.

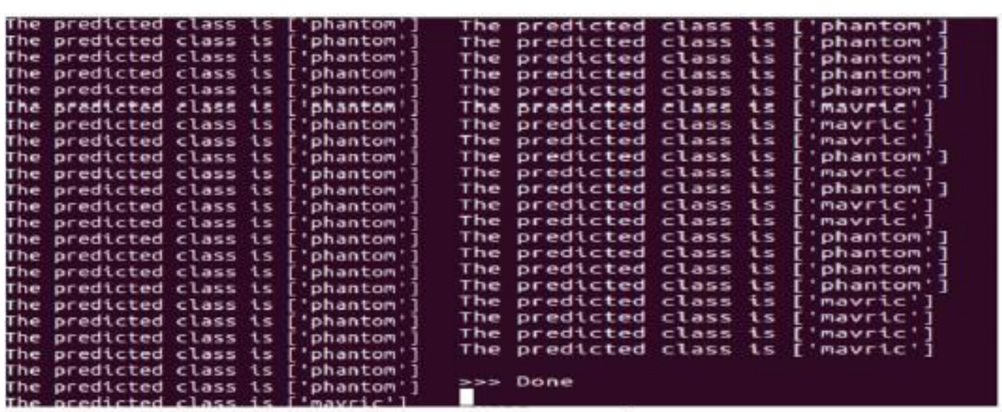
Expected Outcome of Real Time Testing

After implementing the training model and creating a testing le, we need to test the performance of the trained model in real time to also determine its accuracy. When No signal is transmitted, we expect the machine learning result to be:

Figure 9: Prediction output mavic and phantom drone..

Real Time Testing

We carried out a real time detection and classification of drone signal on GNU radio and observed the output of the classification module



a. b.

Figure 10: Prediction output a. when phantom is ON and b. when Mavic is ON.

Drone Detection SNR Testing

In order try to evaluate and test the detection capability of the module RF-class toolbox, we decided to carry out distance analysis test to determine how far away the drone can be from the detection module and its presence not to being detectable even when it is transmitting.

For this test, the Distance between the drone and the detection module was varied and detection data was collected and used for the further analysis.

Figure 11: SNR Test Setup.

Result of Drone Detection SNR Testing

From the distance test conducted we can observe that the detection probability decreases as the drone becomes farther from the detection module. The received signal energy decreases significantly when the drone is away from the module by a distance of 60-100 meters. We can conclude that for now due to hardware capabilities we can only detect the presence of drone under a very good SNR. When the SNR is low, the detection performance also reduces drastically

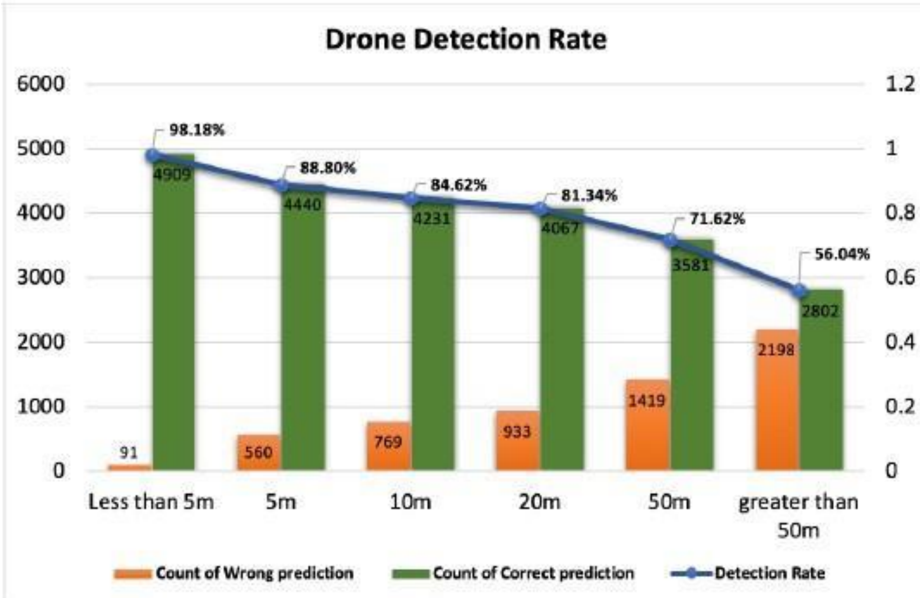
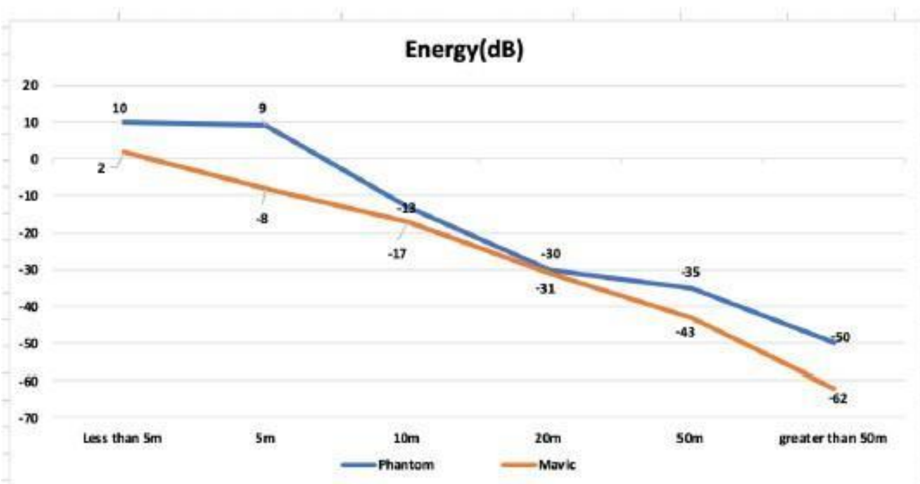
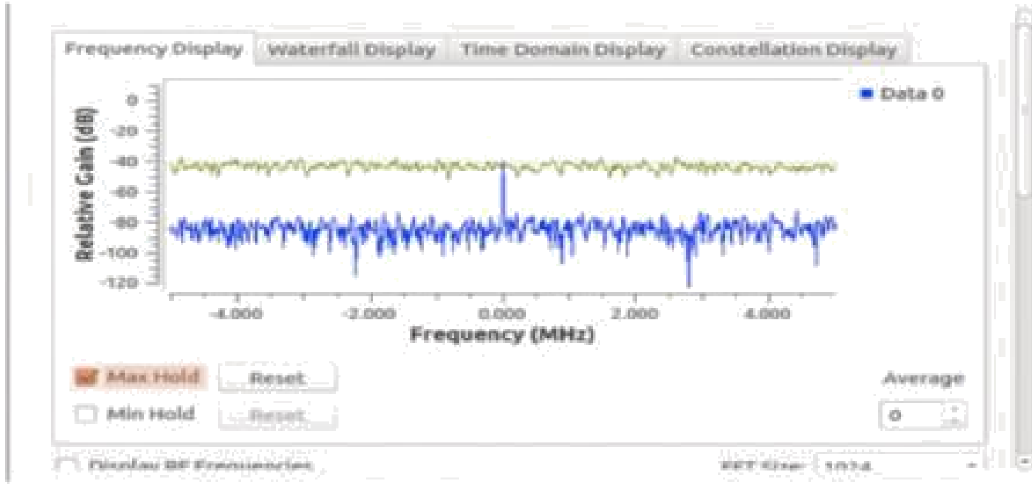


Chart of the detection rate.

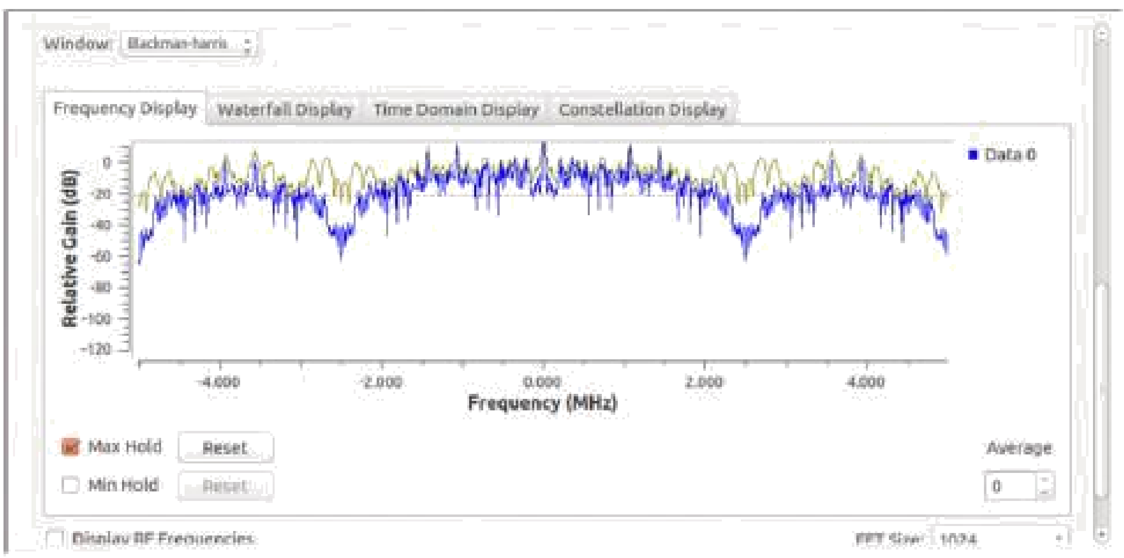


dB plot of the avearage received energy.

Figure 12:

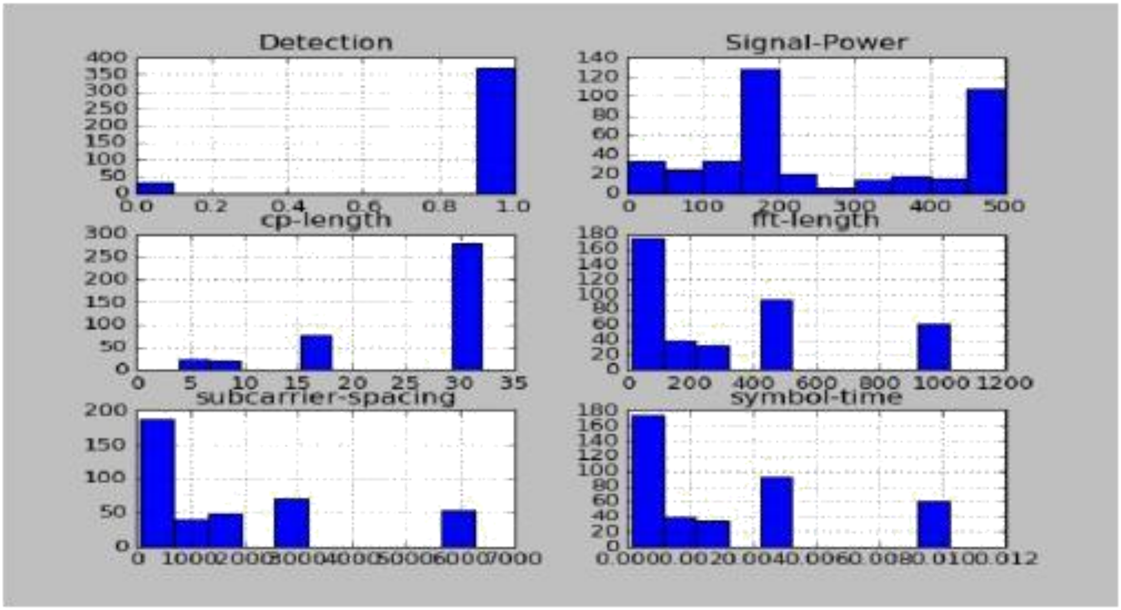


Capture of Energy Detector sink when drone is turned OFF

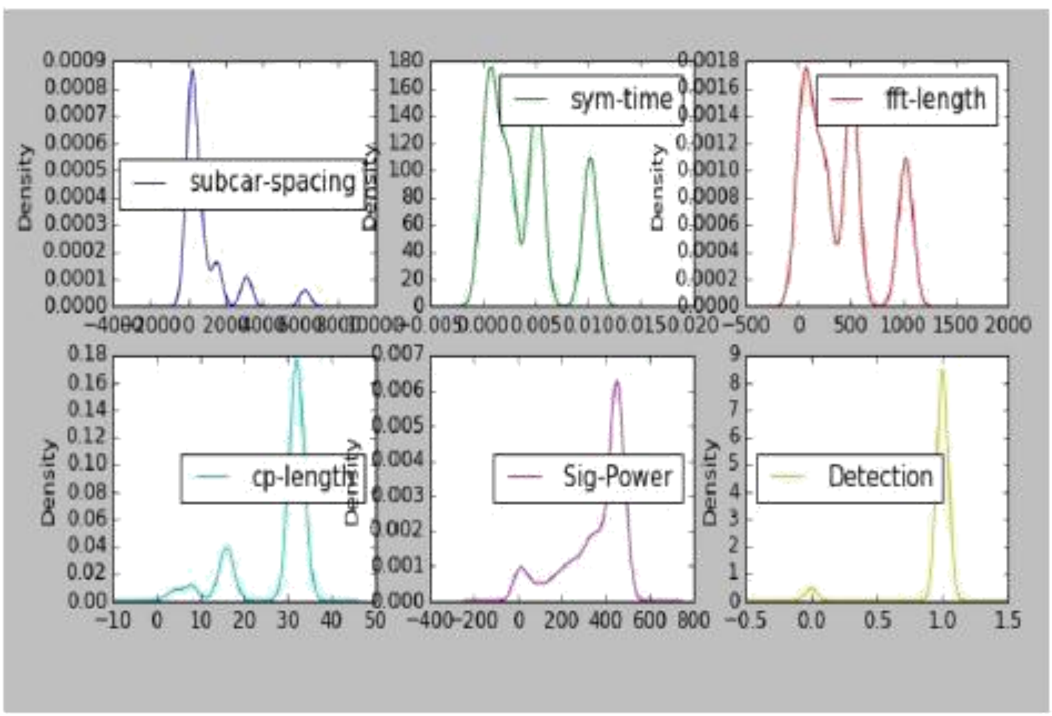


Capture of Energy Detector Sink when drone is turned ON

Figure 13: Energy Detection Output.



Histogram plot of the features



Density distribution of the features

Figure 14:

Discussion:

Overview of Findings

From the experiment and results, we can conclude that drone signal from different class or source can be detected and classified by its radio frequency parameters using machine learning algorithms. This work is still in its early stage, and we hope with more experiment and testing we can improve the overall classification accuracy. GNU Radio Companion was used towards the successful implementation of the drone detection and classification toolbox. We decided to use matlab simulations to validate some of the results and observations of the RF toolbox. Below are some of the initial finding

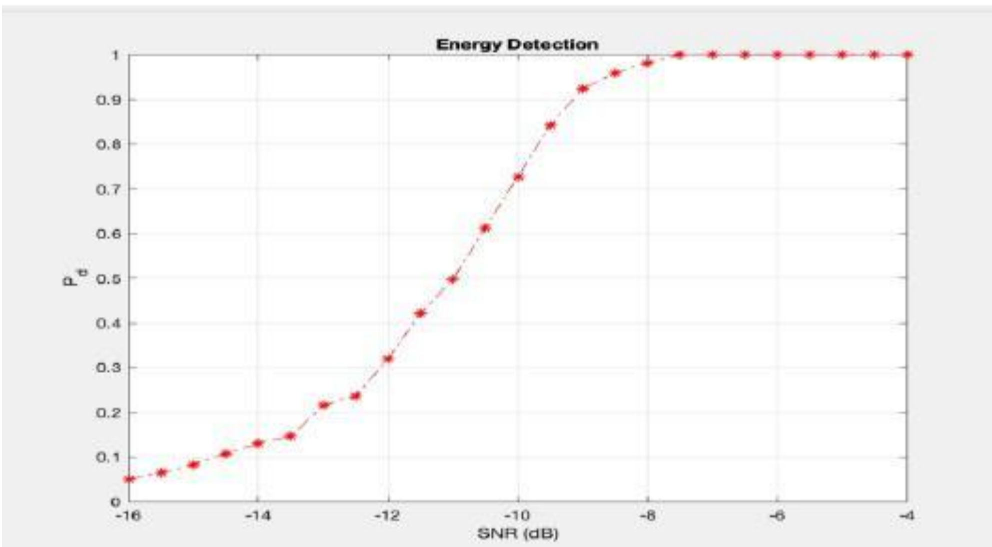


Figure 15: Relationship between Detection probability and SNR.

There is a correlation between SNR and Probability of detection. Detection probability will decrease as the SNR level decreases. In a scenerio where the drone is very close to the receiver, the SNR will be high and this correlates with the results which shows that increase in distance will result in a low detection rate.

Research Limitation

In wireless communications there are different factors that affect the propagation of radio signals from source to destination. In many cases, this is from the antenna transmitting the signal to the receiving antenna. As such for signals to be successfully transmitted and received from one distance to another some factors, play an important role in the design.

A major component is the pathloss, which can be dened as the reduction in the power levels of electromagnetic waves as it propagates through space. Simulation for some different pathloss models that can be associated with wireless signal propagation was done using the matlab tool. Below are some observations. Simulation for some different pathloss model that can be associated with wireless signal propagation was done using matlab tool.

Free Space Propagation Model

Free space propagation model assume the transmitter and receiver are located in an isolated environment and as such effect of reflection or absorption from obstacles are not considered in pathloss estimation.

$$PL = 20 * log_{10}(d) + 20 * log_{10}(f) + 20 * log_{10}((4 * pi)/c);$$

Where the distance d is 1-100 m, frequency f =2.4 Ghz and c is the light speed constant. Ideally, the model is used mostly in cases where the distance in the prediction are in kilometers. But for our experiment the distance is less than 100 meters.

Conclusion:

From the experiment and results shown so far, we can successfully classify signals that are being transmitted from DJI phantom and Mavic drones. Using the machine learning training and testing we observed that out of the different classification algorithms, KNN works best and provide the highest accuracy. Our goal is to be able to improve this accuracy by identifying new features from the test statistics that can be added to the classification model. So far, We have been able to test the addition of signal standard deviation and median and even though accuracy increased a little we think, there is still more to be done in this regard. Real time validation of RF based signal classification using the trained model created from the machine learning algorithm so far has a prediction accuracy which is not very high at this point. And as stated earlier, we hope to change this and intend to continue to carry out more training, testing and analysis so as to increase the prediction of the classification. Different approach will be employed in collecting and testing the data.

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