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Cover Page Footnote

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DETECTION OF ROUGE DRONES BASED ON RADIO FREQUENCY CLASSIFICATION

By Akash V. Gosai* and Sachin Shetty

I. INTRODUCTION

A. Motivation of this research

The Federal Aviation Administration expects the number of Unmanned Aerial Vehicles in the US to be as many as 30,000 (HGH-Infrared). That number continues to grow in parallel to the incidents involving UAVs operating in critical locations. As the costs of obtaining drones is driven down, this research aimed to develop the ability to test and enhance previous drone detection research. There is a need to enhance a current Radio Frequency Signal Classification (RF-Class) toolbox that can detect, monitor, and classify wireless signals (Abdulkabir, 2019). This toolbox's ability to accurately classify signals will provide insights into device fingerprinting. The current classification of RF signals from the drone is achieved by leveraging raw signal information of a specific band. The modulation scheme that was found prevailing in commercial drones is Orthogonal Frequency Division Multiplexing (OFDM). OFDM can be demodulated to provide information about a raw drone signal. This extracted data is coupled with a machine learning algorithm that is used to classify the signal. Testing of this research is needed to identify better equipment and an optimized test scenario that captures quality data that can be used to train a machine learning algorithm.

B. Design of the research

This project is aimed at three key changes consisting of improvement of current drone energy detection algorithm, antenna/SDR improvement, and testing in various environments. The

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current energy detection algorithm did not account for interference or adaptable noise calculations based on the environment. The energy detection algorithm produced a binary result of “1” if a signal was above a pre-determined threshold, meaning a drone signal was present. Conversely, a binary value of “0” would result in a non-drone or no signal present, a calculation below the threshold value. The improved algorithm calculates a simulated noise floor by locating the minimum value of a 2048-value FFT (Fast Fourier Transform). This improved the accuracy of data collection by computing a real number instead of a binary result. Hardware changes evaluated the performance of multiple Software Defined Radios (SDRs). Additionally, the evaluation of antennas with different gains allowed for the range of the system to be improved. For this, both Omnidirectional and Directional antennas were used in comparison. The testing environments used for data collection varied drone-to-receiver distances from 0 to 1000m with and without minor environmental obstructions. Also, the testing scenario included cases for the drone to be tested under load conditions transmitting a video signal to the remote.

C. Thesis statement

The outcomes of this project specifically focused on improvement of the detection algorithm using machine learning, hardware changes to variety of antennas, and application to various testing environments.

II. Overview

A. Improvement of Energy Detection Algorithm

The classification of drones was done by using K-Nearest Neighbor (KNN) machine learning algorithm. This algorithm targets the entire raw dataset and does not require constant learning. KNN is very useful because it allows us to have raw data sets on multiple drones, and it does not restrict the user to only training data for one drone. Once signal energy is captured from the drone using GNU Radio, it can be piped to the machine learning algorithm. KNN searches through the entire dataset for K most similar instances, the neighbor, and summarizes the output variable for those K instances (Brownlee, 2019). To determine which number is closest, a distance is calculated based on the attributes that are classified. For this, the Euclidean Distance (Equation 1) was calculated to approximate the nearest-neighbor search in high dimensional space. Equation 1 possess the qualities to compare two numbers which are more likely to be the same, or when they are farther away their values are less likely to be the same (Yu Hen Hu, 2014). For classification of drone signal, the output can be calculated as the class with the highest frequency from the reoccurring K instances.

$$d(i,j) = \sqrt{(X_{i1} - X_{j1})^2 + \left(X_{i2} - X_{j2}\right)^2 + \cdots + \left(X_{ip} - X_{j}\right)^2} \quad \text{(Equation 1)}$$

The accuracy of the size of the samples will be discussed in the Results. The sample sizes allowed us to include outlier cases in a non-optimized algorithm. The overall process of classification can be split into three steps: data collection, training and prediction. The data collection consists of collecting signal data within the specific environment where the classification will be done. Also, this includes the collection of surrounding noise which we expect when the drone is on. This data will used in the scenario of the drone being turned off as a baseline of ‘no drone’ classification. The training steps consists of turning on the drone and capturing the transmitted energy using GNU Radio. This data will be fed into the KNN algorithm, where the samples will be selected for prediction. The prediction phase is running GNU Radio program with the output model of the training phase to predict new data point calculations.

B. Improvement to Hardware

The original design consisted of the Hack-RF One, type of SDR, with a connected omni-directional antenna for capturing signals. This design was created in the initial research of this system and was to be optimized to run with the Ettus Research’s Software Defined Radio’s.

For this, the evaluation of both the Ettus B205 Mini and B210 were tested with the system. The USRP™ B205mini-i delivers a 1×2 (1 TX and 1 RX) SDR/cognitive radio in the size of a business card [source]. However, the B210 allows for a 2x2 (2 TX and 2 RX) to operate in a full duplex mode, vice the 1x2 half-duplex of the B205 Mini. Table 1 below shows the specifications comparison between all three SDRs. The design chosen is highlighted in bold. Both SDRs have similar coverage but the capabilities of B210 differs due to the dual channel ability for receiving signals. For future usage, the multiple input multiple output capabilities will allow for more data flows to simultaneously occur with an additional connected receiver antenna.

Table 1: SDR Comparison

SDR	Size	Spectrum Coverage	Performance
Hack RF One	Half Duplex	1Mhz–6Ghz	Up to 20 MS/s
B205 Mini	Half Duplex	70 Mhz-6Ghz	Up to 61.44 MS/s
B210	**Full Duplex**	**70 Mhz-6Ghz**	**Up to 61.44 MS/s**

The original antenna (VERT 2450) is an omni-directional antenna which is great for indoor use since it can provide evenly distributed coverage. Omni-directional antennas also work well when the source location is unknown, but at a low gain the signal is less amplified. Since most instances of this research is applied to outdoors scenarios, directional antenna was needed. The directional antenna that provided the best results up to 1 Km was the Tupavco DB541. Table 2 summarizes the specifications of both antennas. The DB541 antenna was successful when it was pointed within 30 degrees on its axis. The results of these antenna comparisons were DB541, and will be shown in section III.

Table 2: Antenna Comparison

Antenna	Coverage	Gain	Polarity
VERT2450	2.4Ghz and 5Ghz	3dBi	Vertically (Omni-directional)
DB541	**2.4Ghz and 5Ghz**	**9dBi**	**Vertically (Directional)**

C. Various Testing Environments

The need for accurate testing conditions that match the war-fighter scenarios is very important. This research accounted for random signals and obstacles in indoors and outdoors. The testing mainly focused on training dataset accuracy, noise and external signal interference, shadowing, the downlink distance and flying under load. Data was split between 80% of training and 20% of validation from the raw captured signal energies. The training set uses the k-fold cross validation, computes a model accuracy then fits the data against the 20%. This process is needed to validate the model which will be ran in the testing environment for classification. Most of the testing occurred outside to simulate possible real-world scenarios. There were three types of testing: pointing the antenna directly at the drone with no obstruction, minimal obstruction, and pointing the antenna about 30 degrees away from the drone. For validation for the first scenario, the drone was not turned on with the model running to check if there was any drone signal or not. Once it was confirmed there was no drone, it would be turned on and flown at different heights. Data would be collected for about 25 thousand points for each distance to keep it consistent. The obstruction scenario was tested by flying the drone over and behind a building with the antenna pointed in the relative direction as the drone. For unknown drone location, testing occurred by pointing the antenna away from the drone by 30 degrees at various heights. The accuracy of the various distances will be discussed in results.

III. RESULTS

The results consist of testing the Mavic 2 Drone in three different scenarios. The three testing scenarios consist of testing in a clear line of sight, shadowing/fading and no line of sight. The line of sight in question is the direction of the antenna pointed towards the drone. Most of the testing occurred in ideal conditions with minimal interference. Both of the tables below use the DB541 directional antenna. Table 3 below shows detection rate up to 150 meters based on random 5000 samples from a pool of 25000 samples for a clear line of sight. The detection rate was derived by dividing the number of true samples by the number of samples multiplied by a 100 to represent a percentage.

Table 3: Mavic 2 Results (Clear Line of Sight)

Number of Samples = 5000			
Distance (m)	Detection Rate (%)	True	False
5	99.98	4999	1
25	99.84	4992	8
50	99.34	4967	33
100	99.46	4963	37
125	98.82	4941	59
150	95.34	4767	233

Table 4 consists of the data of obstructed line of sight. The detection rate of drone or no drone had the accuracy of 80 percent with average drone distance was 150m away. As predicted, the performance decreases as the obstruction and interferences increase. Though the detection rate was improved from the existing setup.

Table 4: Mavic 2 Results (Obstructed Line of Sight)

Number of Samples = 5000			
Distance (m)	Detection Rate (%)	True	False
Shadowing/Fading	88.57	4428	572
Unknown Location	81.22	4034	966

IV. CONCLUSION

This research focused on improvement of the algorithm, hardware changes and testing. The three objectives were met by improving the algorithm, applying a directional antenna, and testing in many different real-world situations. The hardware changes also consisted of a MIMO SDR and directional antenna of 9dBi Gain. The additional testing allowed for having an accurate model to classify a drone up to 1Km.

REFERENCES

Bello, Abdulkabir. "Radio Frequency Toolbox for Drone Detection and Classification" (2019). Master of Science (MS), thesis, Electrical/Computer Engineering, Old Dominion University, DOI: 10.25777/9gkm-jd54 https://digitalcommons.odu.edu/ece_etds/160

Brownlee, J. (2019, August 12). K-Nearest Neighbors for Machine Learning. Retrieved from https://machinelearningmastery.com/k-nearest-neighbors-for-machine-learning/.

Drone/UAV Detection and Tracking. (n.d.). Retrieved January 3, 2020, from https://www.hgh-infrared.com/Applications/Security/Drone-UAV-Detection-and-Tracking.

Ettus Research. (n.d.). USRP B200mini. Retrieved from https://www.ettus.com/all-products/usrp-b200mini/.

Ettus Research. (n.d.). USRP B210 USB Software Defined Radio (SDR). Retrieved from https://www.ettus.com/all-products/ub210-kit/.

Ettus Research. (n.d.). VERT2450 Antenna. Retrieved from https://www.ettus.com/all-products/vert2450/.

Rigby. (n.d.). HackRF One. Retrieved from https://www.sparkfun.com/products/13001.

Tupavco DB541 WiFi Antenna Dual Band - (2.4GHz) and (5GHz/5.8GHz) 9DBI - Medium Range Directional Wireless LAN Network Antenna. (2011). Retrieved January 5, 2020, from https://www.amazon.com/gp/product/B015QEBC4W?pf_rd_p=ab873d20-a0ca-439b-ac45-cd78f07a84d8&pf_rd_r=G57WBCED5EV7R0BCX75B.

Yu Hen Hu. (2014). Euclidean Distance. Retrieved from https://www.sciencedirect.com/topics/engineering/euclidean-distance.