UAV Payload Identification with Acoustic Emissions and Cell Phones

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Abstract: The growing presence of Unmanned Aerial Vehicles (UAVs) in all sectors of society poses new security threats to civilian and military sectors. In response, new UAV detection systems have and are being developed. Current systems use techniques such as Radio Detection And Ranging (RADAR), visual recognition, and Radio Frequency (RF). Another promising solution for UAV detection uses acoustic emissions. Past researchers demonstrated the ability to use UAV acoustic signatures to determine whether a UAV carries a payload and the weight of that payload at close range with high-quality microphones. This research expands the field of study by performing acoustic payload detection using cell phones and at farther range by developing the system called HurtzHunter. The system collects audio data and extracts Mel-Frequency Cepstrum Coefficients (MFCCs) to train Support Vector Machines (SVMs). The HurtzHunter system tests acoustic payload detection with one high-quality microphone and six different cell phones at 7 m - 100 m ground distance from the UAV. At each distance, the experiment runs 6 flights each with a unique payload attached to the UAV. The HurtzHunter design achieves an 88.26% - 99.93% payload prediction accuracy depending on the configuration.

Keywords: Cell Phone, UAV Detection, Mel-Frequency Cepstrum Coefficients, Support Vector Machine, Acoustic Emissions

1. Introduction

Today, there are over 1.25 million Unmanned Aerial Vehicles (UAVs) in operation ranging from $30 to over $35,000 for recreation and industry purposes (FAA 2019) (Kolamunna 2021). This technology brings much excitement, but as with any new technology, UAVs bring new security threats. In 2017, Syrian forces found an ISIS UAV Improvised Explosive Device (IED) plant. The terrorist organization used captured US UAVs to develop their own UAVs and turn them into IEDs (Snow 2017). Moreover, illegal drug traders use small UAVs to ship drugs across the US southern boarder (Wright). In response to these threats, there is an increasing need for UAV detection systems.

1.1 Problem Statement

Current UAV detection platforms focus on Radio Detection And Ranging (RADAR), image recognition, Light Detection And Ranging (LiDAR), or Radio Frequency. Although these platforms are useful, they can be spoofed, and some are limited to direct line-of-sight. Therefore, the need for a new zero-touch, zero line-of-sight acoustic detection system would be useful since UAVs emit acoustics which are more difficult to spoof, do not require line-of-sight, and can be fingerprinted. An effective acoustic payload detection system would allow the identification of a hazardous UAV when other methods do not since heavier payloads stress the UAV's motors more.

1.2 Past Research

Previous work demonstrates the ability to detect the presence of a UAV, the position of a UAV, as well as the payload carried by a UAV using acoustic emissions (Anwar 2019) (Bernardini 2017) (Jeon 2017) (Kim 2018) (Yue 2018). In Traboulisi et al (2020), researchers developed a UAV payload identification system using MFCCs and a Long Short-Term Memory (LSTM) recurrent neural network. For all experiments, the Parrot Mambo Mini Copter was flown indoors with payload weights from 0 grams (g) to 28 g attached. Acoustic emissions were recorded indoors at various ranges (exact distance is not specified in study) using the microphone built into a late 2013 Model Macbook pro. Each sample was processed in MATLAB using a package with a built in LSTM model. Throughout experimentation, white noise from the Gaussian model was added to test different SNR ratios. Their methodology achieved an 87.5% payload prediction accuracy.

In Ibrahim et al (2020), researchers used MFCC components with various Machine Learning (ML) algorithms for UAV acoustic payload identification. Their system collected acoustic emissions with the RodeVideoMicPro (RVMP) at 7 m ground distance from the 3DR Solo UAV. Of the 10 ML algorithms tested for acoustic payload prediction, the Support Vector Machine (SVM) performed the best, achieving an average payload classification accuracy of 98.9%.

At the time of this research, we have not identified any other studies which explore the ability of cell phones to classify UAV payloads from acoustic emissions. This research demonstrates that cell phones can detect and classify UAV payloads from acoustic emissions. In addition, we have not identified any other studies which explore the maximum range for acoustic payload detection. This research tests acoustic payload detection from 7 m to 100 m ground distance, providing novel insight into the maximum range for acoustic payload identification.

2. Technology

This research extracts MFCCs from recorded UAV acoustics, uses the MFCCs to train SVMs for payload identification, and tests the SVMs payload prediction accuracy.

2.1 Mel-Frequency Cepstrum Coefficients

In 1980, Davis and Mermelstein designed MFCCs to digitally describe how the human phonetic system perceives an audio signal (Davis 1980). Today, systems use MFCCs for wireless audio sensor networks, multi-media retrieval, detecting biodiversity metrics in natural environments, terrorist threat detection, home invasion, and much more (Bonet-Sola 2021). MFCCs are a series of coefficients whose values give specific information of what is present in a sound. For example, Artificial Intelligence (AI) uses MFCCs to digitally perceive what a person is saying. Figure 1 shows the process for creating MFCCs.

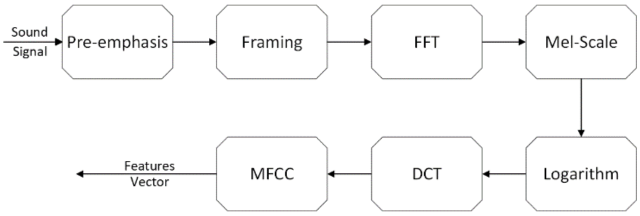

Figure 1: MFCC Generation Process (Ibrahim 2020)

First, acoustic emissions are collected by a recording device; this audio is converted to a digital form. Figure 1 calls this step Pre-emphasis because different microphones prepare the acoustic emissions differently. Once in digital form, the acoustic data is divided into sound constant frames. The frequencies in a sound constant frame do not change. Then a Fast Fourier Transform (FFT) places each frame on a spectrum. After, the spectrums are mel-scaled to reflect human-perceptual changes in frequency rather than just any change in frequency. Next, the logarithm of the amplitude is taken to convert the loudness of each spectrum in a human-perceptually relevant way. Lastly, the Discrete Cosine Transform (DCT) extracts MFCCs from each frame.

2.2 Support Vector Machine

An SVM is a type of ML algorithm which uses hyperplanes to separate classes of data (Kowalczyk 2017). The goal of an SVM is to fit hyperplanes to the data which maximize the margin between classes. Figure 2 shows an SVM with a linear hyperplane.

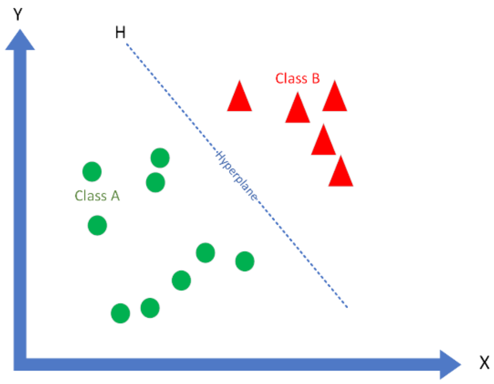

Figure 2: Basic Linear Support Vector Machine

In Figure 2, there is data from two different types of classes. The green circles are data of one class (Class A), and the red triangles are data of another class (Class B). The dotted line is the hyperplane. Each data point has a set of features (x and y) which places it on one side of the line; based on the side it falls on, the SVM knows to which class it belongs. Figure 3 shows the components an SVM uses to generate hyperplanes and learn the difference between classes.

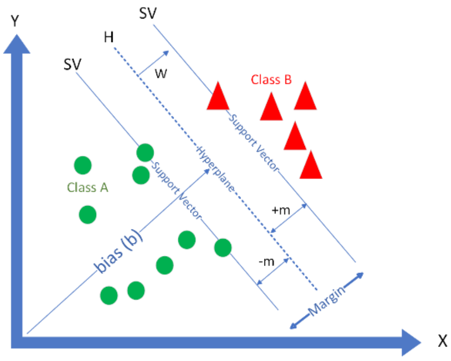

Figure 3: Detailed SVM Graph

The Support Vectors (SVs) are the lines determined by the closest data points from each class to the Hyperplane (H). W (weight) is the normal vector to the hyperplane. The distance from the SVs to the hyperplane is -m and +m. The total distance between the classes is the margin, and the bias (b) is the distance from the hyperplane to the origin. When creating an SVM, the user introduces training data to an SVM with its class identity. In the case of Figure 3, the user introduces the green circles with the identity Class A and introduces the red triangles with the identity Class B. Using the features of each data point (x and y), the SVM plots the data in 2-D space. From here, the SVM fits a linear hyperplane and SVs between the classes which maximize the margin between the classes. After determining the hyperplane and SVs, the SVs satisfy

$$w * x + b = -1 \text{ : For Class A (1)}$$
$$w * x + b = 1 \text{ : For Class B (2)}$$

where x is a vector of the classifiers x and y used to plot the data point, w is the weight, and b is the bias (Kowalczyk 2017). With SVs established, the SVM can categorize new data points using

$$w * x + b = output \text{ (3)}$$

where output determines classification: Class A if less than or equal to -1 and Class B if greater than or equal to 1.

Figures 2 and 3 show data which perfectly fits a hard-margin linear SVM. Hard-margin means there are no outliers, and all data perfectly fits on the correct side of the hyperplane. Due to noise, most experimental data will not fit a hard-margin SVM, so a soft-margin SVM is used. In a soft-margin SVM, the ML is allowed to make mistakes to accommodate outlier conditions which do not fall on the proper side of the SVs. A penalty is given for each mistake, and the SVM chooses a hyperplane which minimizes the number of penalties while maximizing the margin between the data. Even with soft-margin SVMs, a linear hyperplane is often not sufficient to fully classify data, so the kernel trick is commonly employed. Instead of using a linear hyperplane, the kernel trick allows the SVM to use hyperplanes with greater dimensions. Figure 4 shows a linear kernel SVM, and Figure 5 shows a sixth degree polynomial kernel SVM. In Figures 4 and 5, the two different classes are the blue stars and the red triangles. The linear hyperplane was not adequate to properly separate the two classes–a sixth degree polynomial hyperplane is required. Hyperplanes with higher dimensonality are required because many classifiers do not follow linear behavior. SVM kernels exist in every type of polynomial or dimensions. Although the kernel trick fixes this problem, hyperplanes with greater dimensonality create a greater risk of overfitting the data.

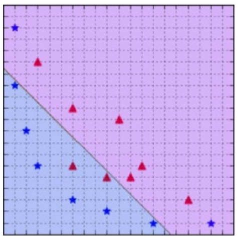

Figure 4: Linear Kernel SVM (Kowalczyk 2017)

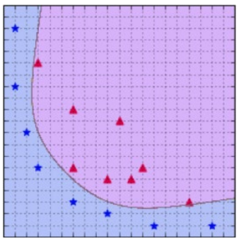

Figure 5: Sixth Degree Polynomial Kernel SVM (Kowalczyk 2017)

3. Methods

This research extends the field of study by focusing on the following questions:

- Can cell phones detect UAV payload weight with sound?
- What is the maximum range of acoustic UAV payload detection?
- Does a high-quality microphone perform better than a cell phone for acoustic payload detection?

3.1 HurtzHunter Design

As shown is Figure 6, HurtzHunter is a UAV detection system which characterizes UAV payloads. Specifically, it uses the acoustic emissions from UAVs to determine the UAV's payload weight. As shown in Figure 7, HurtzHunter conducts payload classification at varied distances and with cell phones. It records acoustic stimulus at 7 m - 100 m from the UAVs. The system uses the following recording devices: three Samsung Galaxy S8s (GS8), one Samsung Galaxy S20 (GS20), one Google Pixel 4 (GP4), one iPhone 11 Pro (iP11P), one RodeVideoMicPro (RVMP). The researchers in (Ibrahim 2020) successfully used the RVMP to create a UAV payload prediction system for close distances; therefore, this research incorporates the RVMP to provide experiment validation and comparison with past research. Unlike the cell phones, the RVMP cannot record and store audio without external audio software and storage. So, the microphone connects to an HP Pavilion business laptop with a 10th Gen Intel Core i5 during recording, and the design stores the audio directly onto the laptop using Audacity (HP) (Crook). To connect the microphone to the laptop, the design uses the TechRise USB External Stereo Sound Adapter Splitter Converter as an analog-to-digital converter (Newegg). The cell phones do not need to be connected to anything while recording.

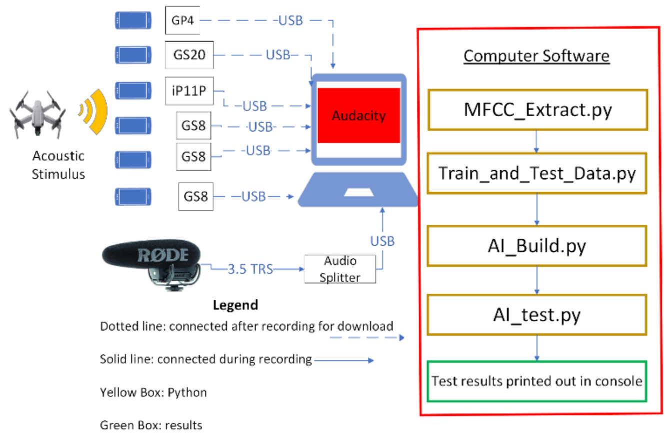

Figure 6: HurtzHunter Design (DJI)

The first phase is recording. The only device connected to the laptop during recording is the RVMP. After recording, the system enters phase two where the system stores the audio recordings on the laptop. In phase two, the user manually connects each cell phone to the laptop one-by-one and downloads the audio files to the laptop. Then, the user manually extracts the RVMP recordings from Audacity to the laptop's file system. Once all the audio files from each device are in the laptop's file system, phase 3 begins. In phase 3, Python version 3.8.8 scripts build SVMs for each recording device from their audio recordings (Python). The user manually runs the scripts in JupyterNotebook (Jupyter Notebook). MFCC_Extract.py uses the Python library librosa to extract the MFCCs for each audio recording and stores the MFCCs in a Pickle file. Then, Train_and_Test_Data.py imports the MFCCs, divides the MFCCs into training and testing data using 5-cross validation, and stores the training and testing data in a Pickle file. AI_Build.py uses the training data to build and train SVMs for acoustic payload prediction using the Python library sklearn. Once trained, the script stores the SVMs to Pickle files. AI_Test.py tests the SVMs with the testing data and prints the prediction results to the console. HurtzHunter uses a 40 millisecond (ms) frame length and 20 ms hop length. This research records acoustic emissions for 60 seconds (s). Therefore, the number of frames for each audio recording is 2999 derived by

$$\#\ of\ frames = \frac{recording\ time}{hop\ length} - 1 = \frac{60}{0.02} - 1 = 2999 \quad (4)$$

In using 5-cross validation, 80% of the data is for training, and 20% is for testing. Each frame results in 1 array of MFCCs resulting in 2999/5 = 599.8 (floored to 599) full MFCC arrays used for testing. Therefore, prediction accuracy (AI accuracy) is (# of correct predictions) / 599.

3.2 Experiments

Figure 7 illustrates the experiment.

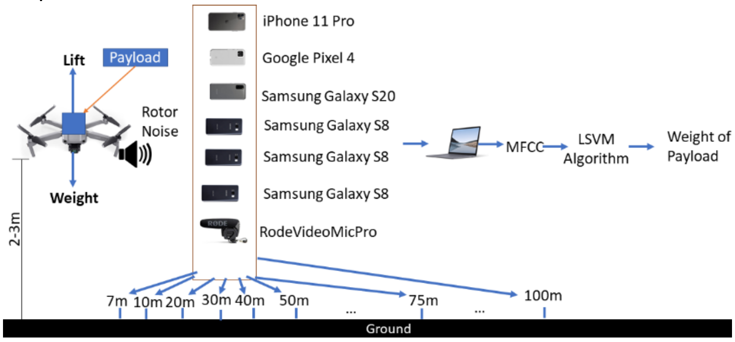

Figure 7: Experiment Diagram (DJI)

All data was collected on a flight line at the Air Force Bombing Range in Avon Park, FL. In the experiment, a DJI Mavic Air 2 hovers 2 m - 3 m above the ground (DJI). While hovering, the 7 microphones simultaneously collect acoustic emissions for 60 s. There are 48 flights in total from which the microphones collect data. The flights are conducted at 7 m, 10 m, 20 m, 30 m, 40 m, 50 m, 75 m, and 100 m ground distance from the microphones. At each distance 6 flights are flown each with a different payload attached to the top of the UAV. The payload weights are 0 g, 56 g, 112 g, 168 g, 224 g, 280 g. The raw data from this experiment is used in 3 different case studies each providing answers to the research questions listed at the beginning of Section 3 Methods. During experimentation, background noise from birds, passing cars, bugs, and wind were present. Wind noise is a major nuisance factor which affected the results discussed in Section 5 Nuisance Factors.

4. Results and Discussion

This academic paper uses the data collected by the RVMP and one of the GS8s. Future work will include the data from the other recording devices shown in Figure 7.

4.1 Case Study 1

The purpose of this case study is to provide experiment validation by repeating experiments in past research Ibrahim et al (2020), and expand the research field by using a cell phone as the recording device. The experiments in Ibrahim et al (2020) used the RVMP as the recording device and collected acoustic emissions from a hovering UAV at 7 m ground distance from the UAV. This study repeats the experiment with the RVMP and one GS8. This case study provides evidence to answer the following questions: "Does a high-quality microphone perform better than a cell phone for acoustic payload detection?" and, "Can cell phones detect UAV payload weight with sound?". This case study uses three SVMs, one with a linear, a quadratic, and a cubic kernel because the experiments in Ibrahim et al (2020) used these SVM kernels. In Ibrahim et al (2020), the researchers achieved prediction accuracy ranging from 98.5 - 98.9 % with their configurations. Figure 8 shows the results from this case study.

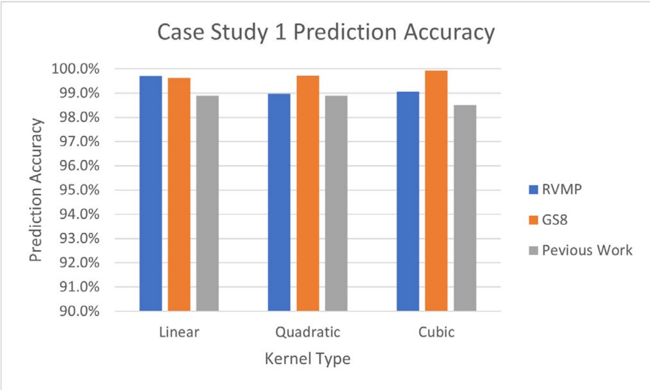

Figure 8: Case Study 1: Prediction Accuracy Results And Comparison

Using the Linear SVM (LSVM), the GS8 achieves 99.62% total accuracy, the RVMP achieves 99.71% average accuracy, and the researchers in Ibrahim et al (2020) achieved 98.9% accuracy. The accuracy for the GS8 and RVMP is the average accuracy across all payload weights. Using the Quadratic SVM (QSVM), the GS8 achieves 99.72%, the RVMP achieves 98.98% accuracy, and the researchers in Ibrahim et al (2020) achieved 98.9% accuracy. Using the Cubic SVM (CSVM), the GS8 achieves 99.93%, the RVMP achieves 99.06% accuracy, and the researchers in Ibrahim et al (2020) achieved 98.5% accuracy. Both the RVMP and GS8 consistently perform with nearly the same accuracy as past research. These results indicate the experiment behaves consistently with past research providing evidence for experiment validation. In addition, the results show that the GS8 performs at the same level as the RVMP. So, there is evidence to suggest a cell phone device achieves the same performance as a high-quality microphone for acoustic payload detection at 7 m. Lastly, the three SVM configurations (linear, quadratic, and cubic kernel) perform nearly the same for the GS8, RVMP, and prior research (Ibrahim 2020).

Table 1: Case Study 1 Runtimes

		1 AI (s)	5 AI (s)
RVMP	LSVM	0.14	0.98
	QSVM	0.52	2.92
	CSVM	0.4	2.43
GS8	LSVM	0.13	0.72
	QSVM	0.38	2.54
	CSVM	0.31	1.69

Table 1 shows the runtime of 1 AI and 5 AIs for each configuration. The reason this study shows 5 AIs is because 5-cross validation requires 5 AIs for implementation. So, the runtime to build all 5 AIs conveys the real runtime to build the AI for HurtzHunter. The runtime for the LSVM is shorter than the QSVM and CSVM for both the GS8 and RVMP. However, the longest runtime is 2.4 s which is relatively short, and does not affect the goals of this research.

4.2 Case Study 2

Case Study 2 builds upon Case Study 1 by increasing the distance between the microphone and UAV from 7 m to 100 m. Previous work gathered acoustic emissions at 7 m away from the UAV. This research expands the field of study by gathering acoustic emissions at 7 m to 100 m away. This study uses the one GS8 (from Case Study 1) and the RVMP to collect acoustic data at 7 m, 10 m, 20 m, 30 m, 40 m, 50 m, 75 m, and 100 m ground distance from the UAV. Additionally this case study builds an LSVM, QSVM, and CSVM for each recording device. The results in this case study provide answers to the questions "What is the maximum range of acoustic UAV payload detection?" and, "Does a high-quality microphone perform better than a cell phone for acoustic payload detection?" Figure 9 shows the prediction accuracy for all three SVMs using the RVMP.

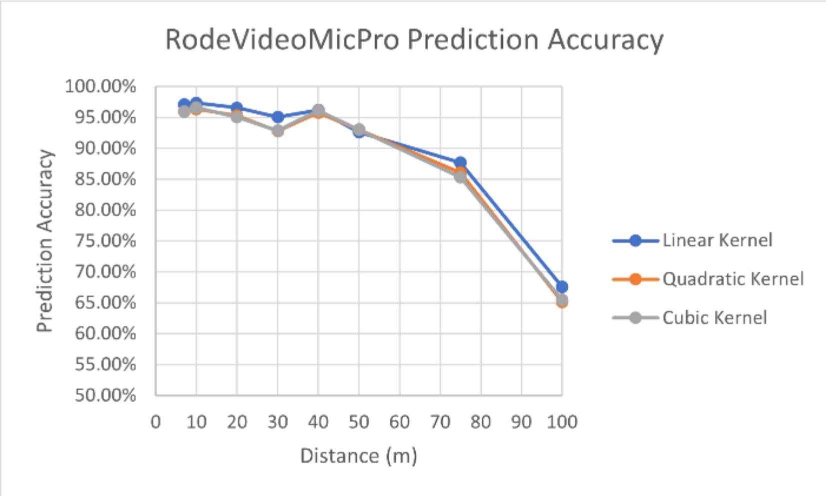

Figure 9: Case Study 2: RVMP Three SVM Comparisons

Using the RVMP, the average accuracy across all distances and payloads for the LSVM is 91.27%, for the QSVM is 90.05%, and for the CSVM is 90.05%. As Figure 9 shows, the prediction accuracy remains above 90% from 7 m - 50 m, then declines. Case Study 1 shows a total accuracy of 99%. When all distances are included, the average accuracy decreases to 90.05% - 91.27%. This decrease is expected due to the loss of signal strength as distance increases. A sound is fainter at longer distances and stronger at shorter distances, and fainter sounds are more difficult to capture with a microphone. Therefore, a weaker signal should lead to a decrease in prediction accuracy because it carries less information. The results in Figure 9 support this phenomenon as the percent accuracy decreases as distance increases. Specifically, the main decrease is from 50 m to 100 m. In addition, the signal strength does not affect the prediction accuracy until after 50 m. Therefore, there is evidence to suggest the maximum range for acoustic payload detection is 50 m.

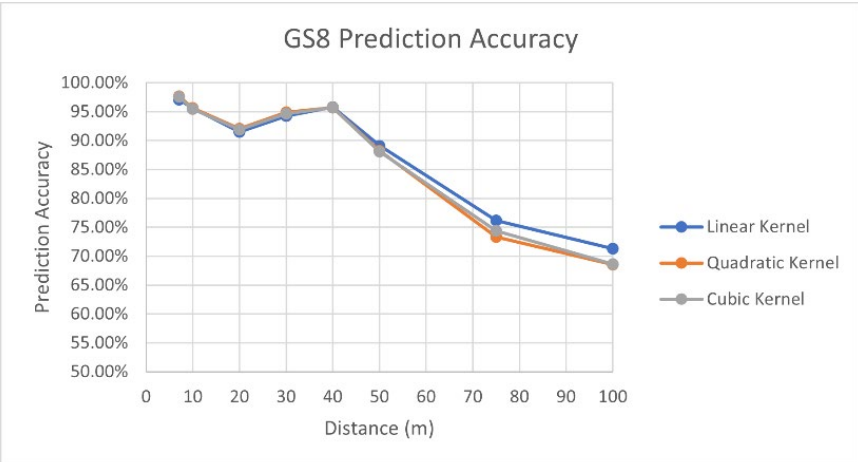

Figure 10: Case Study 2: GS8 Three SVM Comparison

Figure 10 shows the prediction accuracy for all three SVMS using the GS8. The average accuracy across all distances and payloads for the LSVM is 88.84%, for the QSVM is 88.26%, and for the CSVM is 88.30%. As Figure 10 shows, the prediction accuracy remains above 90% from 7 m - 40 m, then declines. Case Study 1 shows a total accuracy of 99%. When all distances are included, the average accuracy decreases to 88.26% - 88.84%. As observed from the GS8, loss of signal strength leads to a decrease in prediction accuracy, but there is not a significant drop in accuracy until after 40 m.

Table 2 shows the runtimes for the RVMP, and Table 3 shows the runtimes for the GS8.

Table 2: Case Study 2 RVMP Runtimes

		RVMP Runtime		
		Seconds	Minutes	Hours
Linear	1 AI	3781.8	63	1.1
	5 AI's	19971.6	332.9	5.5
Quadratic	1 AI	224.6	3.7	0.1
	5 AI's	1086.5	18.1	0.3
Cubic	1 AI	205.6	3.4	0.1
	5 AI's	1061.6	17.7	0.3

Table 3: Case Study 2 GS8 Runtimes

		GS8 Runtime		
		Seconds	Minutes	Hours
Linear	1 AI	7831.9	130.5	2.2
	5 AI's	34541.9	575.7	9.6
Quadratic	1 AI	257.6	4.3	0.1
	5 AI's	1357.5	22.6	0.4
Cubic	1 AI	264.5	4.4	0.1
	5 AI's	1324.1	22.1	0.4

In Case Study 1, the runtime was less than 3 s. In this Case Study, the runtime to fully classify a LSVM increases to 5.5 hours (hrs) for the RVMP and 9.6 hrs for the GS8. The reason for this change is because the AI in this study uses data from all ranges (7 m to 100 m) which is seven times the data Case Study 1 uses. In addition to the amount of data, the nature of the data in this case study is more difficult to classify than the data in Case Study 1. Due to factors such as range, loudness, and wind noise, the SVM needs more hyperplanes to fully classify the data. This result indicates a higher degree kernel is ideal to fully classify the SVM.

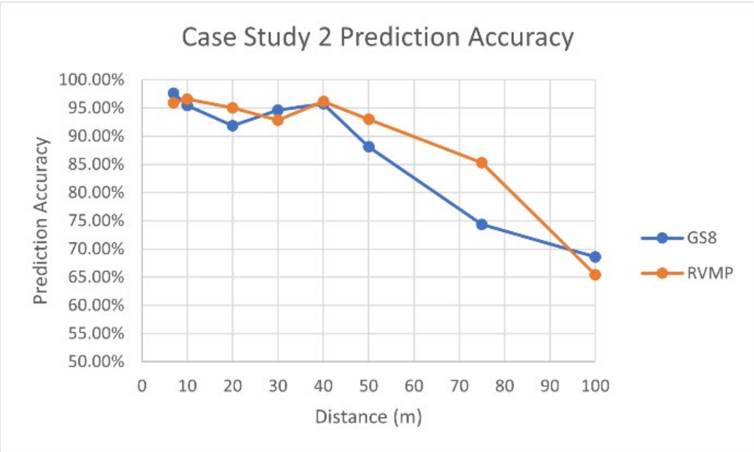

Figure 11: Case Study CSVM Comparison

The Quadratic and Cubic SVMs have higher dimensionality, so their hyperplanes are able to better classify the data. Because all three kernel configurations for the SVM follows the same results, this research concludes the CSVM is the optimal configuration due to its high accuracy and short runtime. Therefore, this section compares the CSVM for the RVMP and GS8. Figure 11 shows the CSVM for the RVMP and GS8. The graph shows that there is not an optimal device for all distances. It shows that the cell phone performs relatively the same as a high-quality microphone. Additionally, both devices observe a drop-off in prediction quality after 40 m.

5. Nuisance Factors

The three largest nuisance factors are wind, time of day, and battery life. Wind and time of day affect the prediction results. These factors were uncontrollable in the experiment. Only two UAV batteries were available and one battery charger available on the flight line. Each battery provides ~12 min of flight time, and it takes 2 hours to charge a battery. So, the recordings were spread out over the day. The different times of flight affected the experiment results because the winds varied throughout the day. Recordings done during high winds show lower prediction accuracy than those during low winds. Figure 12 shows the prediction accuracy over time of day. The figure shows results from the GS8 in Case Study 2. All devices show this same trend.

The order of weight classes was randomized. The order is as follows: 280 g, 0 g, 168 g, 224 g, 56 g, 112 g. Therefore 280 g and 0 g were ran in the morning, 224 g was ran around noon, 56 g was ran in the early afternoon, and 112 g was ran in the late afternoon. Winds were calm in the early morning and began to pick up around mid morning peaking in the early afternoon; they started to trail off in the mid afternoon. Figure 12 shows how accuracy changed throughout the day and that there is a direct correlation between wind and accuracy. Table 4 shows the wind noise readings for each weight. The experiments use the iOS National Institute for Occupational Safety and Health (NIOSH) Sound Meter app to measure ambient noise (EA Lab). The Center for Disease Control (CDC) developed this app to measure ambient noise in dB (CDC). Right before each flight, the researcher used this app on the iP11P to measure the ambient noise in dB.

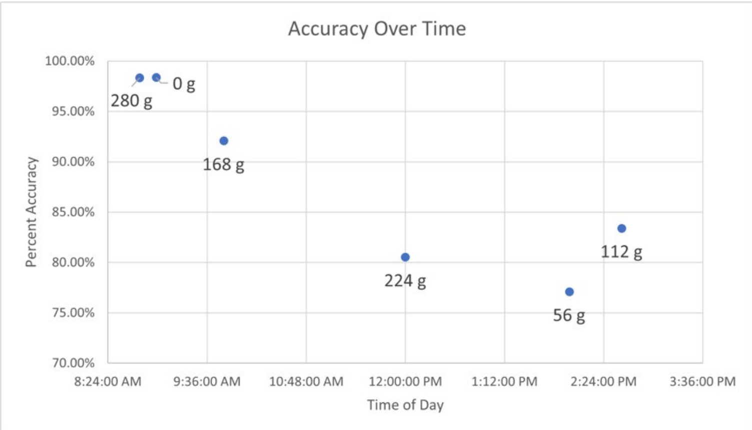

Figure 12: Prediction Accuracy Over Time of Day

The results shows wind noise has a clear effect on the system. When the noise level is below 50 dB, the system remains fairly accurate, but at or above 54 dB there is a significant decrease in accuracy. The wind noise begins todrown out the UAV acoustic emissions somewhere between 50 dB and 54 dB. Further research needs to find the exact threshold.

Table 4: Wind Noise

Weight (g)	Wind Noise (dB)	Time of Day
280	44	8:47:00 AM
0	45	8:59:00 AM
168	49.7	9:48:00 AM
224	55.4	12:00:00 PM
56	62.5	1:59:00 PM
112	54.7	2:37:00 PM

6. Conclusion

This research demonstrates the ability to use UAV acoustic emissions to identify payload weight at up to 100 m away from the UAV with cell phones. This research developed the HurtzHunter design to demonstrate the ability to use cell phones for payload detection. Based on the configuration, the procedures demonstrated in this research are capable of achieving a payload prediction accuracy between 88.26 - 99.93% depending on the configuration.

Acknowledgments

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