Software Define Radio based Intruding UAS Group Behavior Prediction

Joshua Eason
Department of Mathematics
Creighton University
Omaha, Nebraska, 68007
Email: Josheason@creighton.edu

Chengtao Xu and Houbing Song
Department of Electrical Engineering and Computer Science
Embry Riddle Aeronautical University
Daytona Beach, Florida, 32119
Email: xuc3@my.erau.edu songh4@erau.edu

***Abstract*—With the advancement of unmanned aerial vehicle (UAV) technology, UAV swarm has been showing its significant security threats towards the ground facility. With current technologies, it is still challenging in unknown UAV swarm tracking and neutralization. This paper proposes an analytical method in predicting drone flying behavior based on the machine learning algorithm, which could be integrated into swarm behavior prediction. Radio frequency (RF) signals emitted from the UAV are captured by software-defined radio (SDR) to form the time series data. Using conventional short-time Fourier transform (STFT), a time-frequency spectrum revealing the RF data energy distribution is obtained to analyze the signal variance pattern formed by the two different types of UAV flying trajectory. The transformed time-frequency domain matrix would be applied in multiple machine learning classifiers to tell the different flying trajectories. The results present the applicability of using machine learning in predicting the flying features and modes of intruding UAV swarm. It shows the potential of enhancing the redundancy of the UAV negation system.**

***Index Terms*—UAV Trajectory Tracking; Machine Learning; STFT; Software Defined Radio**

I. Introduction

A fast-growing UAS market nowadays has made significant impacts in most aspects of modern society. For example, a UAV based transportation platform advances the package delivery of post service, which shows its great convenience and efficiency in reducing human resources, energy fuel costs brought by conventional human labor centered industries. Thanks to the advanced technologies developed in manufacturing, control, and communication, the amateur drone has also shown excellent potential to be involved in ordinary entertainment. However, significant threats underlying this flourishing expansion of the UAV market also generate air transportation security issues. As reported, over 100 airport incidents have claimed that it is related to obscene UAV in the past year, which catches much attention from federal government organizations, such as FAA, DOHS, to develop effective technology or system design to mitigate unknown, intruding UAVs.

To effectively neutralize the intruding amateur UAV in essential facilities, such as airport, nuclear power plant, existing technologies mainly focus on the physical suspension of objects using aerial-based net capturing [1] anti-drone net gun. With the evolution of machine learning and advanced RF jamming technologies, even more advanced UAV detection, analytics, and jamming methods have been integrated into real platforms [2]. However, a manual jamming platform with human operation assistance could still have its defensive vulnerabilities while facing a precisely planned attacking plan. For example, a successive UAV intruding with multiple operators is not applicable to be ceased by a limited number of the jamming operator in the field. A more difficult defending situation in the not far future would appear with the evolving technologies in UAV swarm, making the technologies existing nowadays not applicable anymore in suspending one UAV at a time. A more autonomous anti multiple drone platform is needed.

This paper proposes an analytical method in predicting drone flying behavior based on the machine learning algorithm. Radio frequency (RF) signal emitted by the UAV is captured by software defined radio. Using conventional short time fourier transform (STFT), a time-frequency spectrum revealing the RF data energy distribution is obtained to analyze the signal variance pattern formed by the two different types of UAV flying trajectory. The transformed time-frequency domain matrix would be applied in multiple machine learning classifiers to tell the difference of different flying trajectories. The result would show the potential applicability of using machine learning in predicting the flying trajectory of intruding UAV.

RF signal is applied in most of the communication between UAV and its controller, which creates a unique wireless link compared with the environment noise [3] [4] [5]. In [6], various SNR value with RF intrinsic energy distribution gives the threshold of classification on detecting the presence of the drone. [7] gives the method in classifying the number drone when SDR receives signals from a group of UAVs based on an indoor test environment. UAV's transient signal gives us enough information on UAV operation mode's kernel features, distance from the detector, speed, etc. Unlike the transient signal fraction method, which is involved in feature extraction, the transient signal's energy distribution creates more typical features in classifying the number and presence of UAVs [8] [9].

The remainder of this paper is structured as follows. In section II, the background of RF signal detection mechanisms is given. Section III explains the experiment set up and the SDR signal receiving module configuration. Section IV presents the results of the UAV flying trajectory classification. Finally, in section V, we conclude our paper and give future research direction.

II. Background

A. Radio Frequency Signal Variance

The first personal view (FPV) on UAV uses a radio frequency antenna to transmit vision data from drone to a remote controller or monitor. In transmission, two antennas are adopted typically for different UAVs based on the application: omnidirectional antenna and directional antenna. The omnidirectional antenna radiates radio wave power uniformly in all directions in a single plane, with the radiated power reducing with the increase in its absolute elevation angle. The following two equations give the electro-magnetic radiation value in the far field.

$$E(\bar{r}) = j \times k \int_{v} \left[\hat{R} \times \overline{M}\left(\bar{r}, \bar{r}'\right) \right] \left(1 + \frac{1}{jkR}\right) G(\bar{r}, \bar{r}') d\bar{r}' \tag{1}$$

$$\bar{H}(\bar{r}) = jk \int_{V} \bar{J}\left(\bar{r}'\right) \times \hat{R} \left(1 + \frac{1}{j\kappa k}\right) G(\bar{r}, \bar{r}') \tag{2}$$

in which, $G(\bar{r}, \bar{r}^{prime})$ could be denoted as:

$$G\left(\bar{r}, \bar{r}'\right) = \frac{\bar{e}^{jk|\bar{r}-\bar{r}'}}{4\pi\left|\bar{r}-\bar{r}'\right|} = \frac{e^{-jkR}}{R} \tag{3}$$

Equation $(1), (2), (3)$ give the variance relation between the observation point and source point. Therefore, with the increasing of R, $\bar{H}(\bar{r})$ and $E(\bar{r})$ decreases. The radio signals are broadcasting from a location, and the signal radiates out from the transmitter with a decreasing level of EM field strength as the distance increases. The magnitude of the radio signal shows up in the frequency spectrum after FFT has a bigger value. Similarly, radio signal strength would become weaker, or the wireless link would be lost as the signal receiver and transmitter move away from each other. While the radio signal transmitter moves relatively towards or further away from the signal receiver, the doppler effects and wireless signal EM field changes could cause the variance of signal magnitude emitting frequency. Therefore, different flying modes with various approaching trajectories relative to the receiver would generate a rich amount of pattern in determining intruding UAV features.

B. Transient Signal Energy Distribution

The transient signal's energy distribution over the time-frequency spectrum could reveal the instant signal strength dynamics over different frequency components. Short time fourier transform (STFT) provides one of the ways to represent this transient signal spectrogram by calculating the magnitude of signal as follows,

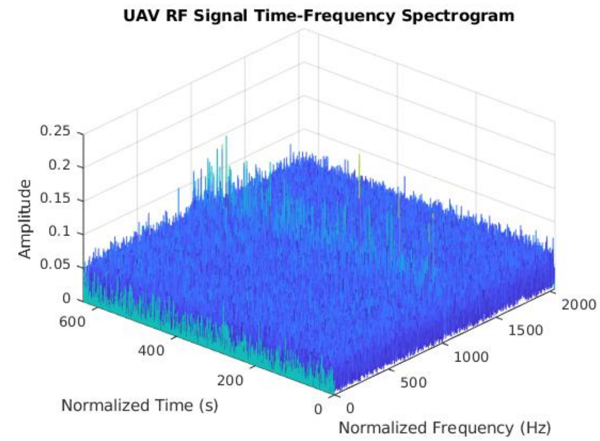

Fig. 1. Spectrogram of UAV RF Signal

$$STFT(f,t) = \sum_{n=-inf}^{inf} s(t)w(t-m)e^{-}j2\pi kn/N \tag{4}$$

where s(t) indicates the received RF signal, $w(t)$ denotes the discreet window function, n represents the sample number, and N is the FT analyzing window. Index m is the positions of the analysis window, in which $m(i-1) = m(i) + nN$. k indicates the index of frequency components kw_0 where $w_0 = 2\pi f_s/N$.

Fig. 1 shows the signal energy distribution over the time-frequency spectrum of the UAV RF signal. By ignoring the noise signal except the main radio transmission components, an apparent signal strength variance could be seen on the 1020 - 1029 Hz frequency interval, corresponding to the signal variance pattern of UAV straight flying trajectory in the following section.

III. Experiment Configuration and Time Series Signal Pattern

In this section, the experiment setting and a captured video signal from the UAV transmitter would be discussed over a time sequence. It represents the difference in signal magnitude variance pattern over two different flying trajectories.

RF signal capturing was done in the DBRCA test field, which includes a 100 meters flying track and a signal receiving site with 35 meters perpendicular distance away from the runway. Besides the existing wireless signal over the ISM band, there is no external signal inference over 5.8 GHz, which is the centering frequency of UAV video signal transmission. Two types of flying trajectory experiments are used to illustrate the difference of the signal variance pattern.

A. Straight Flying

As shown in fig. 2, the UAV flight follows the straight flying trajectory along with the flight track. The emitted RF signal was received by the USRP N310. Green lines mark the flying trajectory of UAV with two times the length of the runway. According to the eq.(1)(2)(3), we could assume that the signal strength of UAV varies with the variance of Euclidean distance between UAV and USRP devices.

Fig. 2. Straight Flying Trajectory along with Run Way

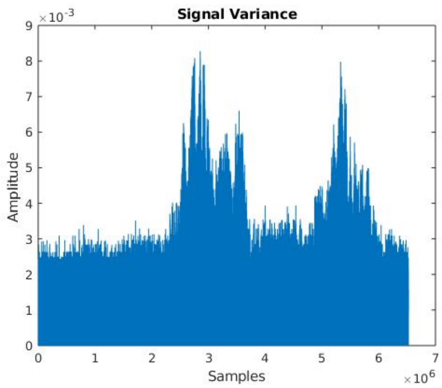

Fig. 3. Signal Amplitude Variance with UAV Straight Flying Trajectory

Fig.3 shows the same signal variation pattern as our assumptions above. The first time series signal pitch was generated by the first time of UAV approaching the signal receiver. Then the amplitude drops after the dropping of the distance between the signal emitter and SDR receiver. Similarly, the second shorter pitch was made while the UAV is on its back way.

B. Round Flying Surrounds Signal Receiver

In fig. 4, green lines mark the circling flying trajectory of UAV with the same radiance. Similarly, as straight flying mode, we could assume that UAV's signal strength varies with Euclidean distance between UAV and USRP devices. Therefore, the signal strength should keep on the same level over the sampling period. However, due to the variance of different initial speed and not exact round flying trajectory, the signal amplitude over time series could not follow the perfect steady value.

Following the same pattern as we assumed of round flying, the strengthening of signal amplitude over 0.3×10^7 samples could be introduced by the initial approaching phase. Simultaneously, UAV could not hold a perfect tangent velocity, which causes the factorized speed towards the signal receiver. Besides that, the time-series signal holds a minimal amount of variance over the rest amount of the sample points.

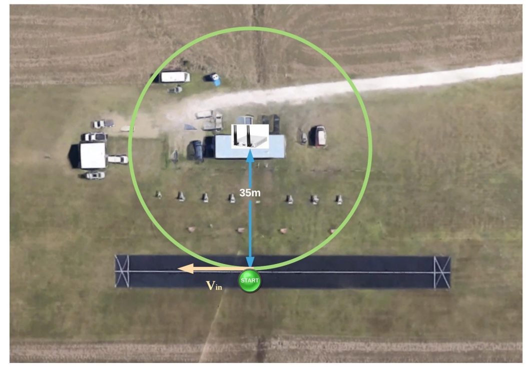

Fig. 4. Round Flying Trajectory

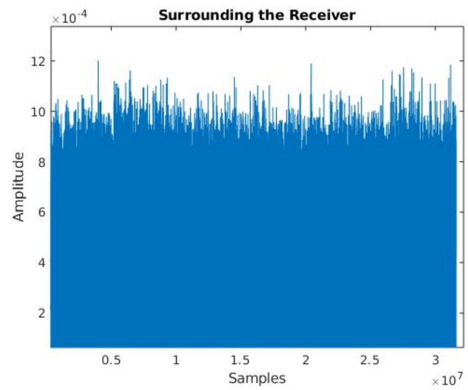

Fig. 5. Signal Amplitude Variance with Round Flying Trajectory

C. Data Augmentation

Each flight captured by the spectrogram during the experimental phase was considered to be one "event" on which we were interested in classifying the UAV flying behavior. In order to best model the behavior, each flight was treated as a 2D image matrix consisting of 308 rows of time-series observations, and 2048 signal feature columns representing each of the available frequencies of captured data. The data was then augmented by selecting eight of the ten signal features across the spectrum corresponding to the significant features identified in fig. 1. Once selected, the eight signal features were shifted to each of 256 possible positions within the matrix, creating an additional 255 images of data, with variation in signal location within the data. This was done for each of the eight available flight images, which allowed us to expand our set of images to a total of 2048.

IV. Results and Discussion

In this section, the spectrogram pattern's classification result from two different flying trajectories would be presented. We would discuss the spectrogram pattern's matrix form in 300× 2048 size, which represents 2048 frequency points with 300 time samples. By each column of the data representing the signal variance overtime at each frequency point, fig.1 shows that only 1020-1029 columns have the actual signal strength variance in the process of video signal packet delivering. Therefore, ten columns of the data were picked as the features in the process of UAV flying mode classification. Three groups of straight and surround flying data sets have been selected as the training data, and 1 of each flying trajectory set has been selected for verifying the classification result of the neural network model.

Such a flying trajectory difference classified by the machine learning algorithm falls into a typical binary classification problem. Table. I shows the great accuracy in classifying two different time series data patterns over ten picked frequency points. With a similar spectrogram matrix, pattern and less noise from radio interference added to the received radio signal that we have seen in fig. 3 and fig. 5, this significantly high accuracy of binary classification is expected. However, the result gives an idea of the received signal strength indication (RSSI) variance could be a vital criterion for detecting amateur UAV presence. With the evolving technology of autonomous vehicles, less constantly emitted RF signals could be applied as the detection resources for investigating UAV in the secured field. The UAV could still send the intermittent signal for flying trajectory verification to the remote controller for considering the redundancy of UAV fly control system design. Therefore, this paper gives out the result that uses the emitted video signal to verify the potential of SDR in detecting the Doppler effects and RSSI variance of the UAV transmission signal. A fully autonomous UAV swarm shares the same detectable signal characteristic.

	KNN	MLP	SVM	DT
Accuracy	1	1	1	0.95826
Accuracy for 1	1	1	1	0.934615
Accuracy for 0	1	1	1	0.979381
Running Time(s)	13.934	1.189	3.796	4.016

TABLE I

BINARY CLASSIFICATION ACCURACY OF MULTIPLE CLASSIFIER

Further considerations of comparing this UAV detection method with other conventional real-time flying trajectory tracking techniques, such as active radar, microphone array formed detection field, RF signal tracking. This method gives a unique viewpoint of using significantly fewer data to recognize the UAV flying path by the initially less amount of data signal variance data on RSSI and doppler effects, which provides fewer data processing time and lower false positive rate detection. It gives the UAV detection and negation system enough time to evaluate the intruding objects' threats in the secured field.

V. CONCLUSION

This paper gives out the UAV flying mode classification result by using a machine learning algorithm. The RSSI variance and doppler effects brought by the different moving trajectory of UAV could be served as the detection resources by recognizing the signal amplitude pattern on the time-frequency domain. The final result of binary verification gives great accuracy in verifying the ability to recognize the signal pattern on a trained neural network. A similar method could be applied in detecting a moving object with a dynamic pattern of the emitted signal.

In future work, predicting the UAV flying trajectory is needed to be investigated based on the machine learning technique. The physical distance data between signal emitted source and SDR should be obtained in the field test, designed as another feature of neural network training. It enhances the UAV detection system ability in the accurate UAV trajectory tracking and positioning, which extends the system's redundancy in the time of threat evaluation and neutralizes suspicious intruding objects.

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