3rd URSI AT-AP-RASC, Gran Canaria, 29 May – 3 June 2022

Drone Classification with a Convolutional Neural Network Applied to Raw IQ Data

S. Kunze(1), B. Saha(1)
(1) Deggendorf Institute of Technology, Freyung, Germany

Abstract

With the increasing popularity of civilian drones, the need for technical detection and classification systems rises. In this paper a machine learning based approach for detection and classification of radio frequency signals from drones is proposed. As data source the DroneDetect_V2 data set is used. The raw IQ data is processed by a convolutional neural network, without the need for much pre-processeing or any feature engineering. With this approach an accuracy of 99 % for detection and between 72 % and 94 % for classification is reached.

1 Introduction

Civilian unmanned aerial vehicles (UAVs), commonly known as drones have matured from recreational niche products to commercially used systems with a wide range of applications. With the rising popularity and increasing numbers of drones in the sky, security and safety issues become a pressing concern. The safe integration of UAVs into the airspace requires both standardized regulations, as well as technical solutions (such as transponder systems). However, even with a standardized integration into the airspace, drones can nevertheless pose serious threats. Due to technical and human errors or intentional misconduct, these safety regulations can be eluded. Drone detection and classifications systems, which don't rely on the cooperation of the unmanned aerial system (UAS) (e. g. by transmitting position and drone type through a transponder) are required to protect critical infrastructure objects, such as airports. Different technologies such as audio, video, radar or radio frequency (RF) scanners have been proposed for this task. In this paper one approach for detecting and classifying drones based on their RF signals is presented. A convolutional neural network (CNN) is used to analyze the raw in-phase and quadrature (IQ) data stream, without requiring much pre-processing (with the exception of windowing and normalization).

The work discussed in this paper is part of the project SIMULU. The acronym is short for "Sicherheit im unbemannten Luftraum" (German for "safety in the unmanned airspace"). The project focuses on different aspects for the safe integration of civilian UAS into the lower airspace. It addresses regulatory questions and technical solutions for cooperative drones. A prototypical geo-awareness-system shall combine the functionality of a transponder system with a warning and guidance system for human drone pilots or the possibility of temporarily taking over autopilot guided drones. The handling of uncooperative drones is also one aspect which SIMULU addresses. One part of this, is machine learning (ML) based approach for detecting and classifying radio signals from UAVs.

In this paper the approach for the detection and classification or RF signals from drones is proposed. In the next section of this paper a short look at some related work in this field of research is given, followed by description of the used data set. In section 4 the used approach is discussed before initial results and a look ahead at the future work is presented in sections 5 and 6 respectively.

2 Related Work

A more detailed literature review on machine learning applications for drone detection and classification is available from Taha and Shoufan [1]. The authors consider machine learning based classification for radar, visual data, acoustic data and radio frequency based systems. Shi et al. propose a system for detection of small UAVs in the 2.44 GHz frequency band based on hash fingerprints and distance-based support data description (SVDD) [2]. Another approach using different algorithms to detect UAVs based on their physical attributes is presented by Nguyen et al. [3]. Wavelet analysis is used to detect body shifting caused by the spinning propellers and power spectral density (PSD) through a short-time Fourier transform is used to detect body vibration. With this, a RF signature of the UAV is created. Enzuma et al. present a system for detection and classification of 14 different UAV controllers [4]. For detection, raw RF signals are converted into the wavelet domain and than classified by a naive Bayes classifier based on Markov models. For classification, features are selected using a neighborhood component analysis on energy transient signals. Finally, these are analyzed with various machine learning algorithms for classification. Medaiyese et al. propose a semi-supervised Framework for UAV detection, using wavelet analysis. A accuracy between 86 % and 97 % was achieved, depending on the signal-to-noise ratio [5]. Allahham et al. created their own data set of UAV RF signals [6]. The time-series samples from the data set are transformed into the frequency domain and then classified by three deep neural networks with two classes (drone detection), four classes (drone type) and ten classes (drone type and flight mode) respectively [7]. The same data set is used by Zahng for a comparison of six different machine learning models for drone detection [8]. The author also follows the same approach of transforming the data from time to frequency domain before applying the machine learning models. It is concluded that XGBoost shows the best performance of the eventuated models.

A method for classification of drone signals using a pre-trained neural network and transfer learning is proposed by Swinney and Woods [9]. The RF samples from the drone are used to calculate a spectrogram or PSD respectively, with a fast Fourier transform (FFT) size of 1024. Using Python and the Matplotlib library images with a resolution of 224x224 pixels are created. These serve as input for a pretrained VGG16 CNN. This neural network has 13 convolutional and five pooling layers. It's pre-trained on ImageNet for feature extraction. This approach was previously used in other fields such as medical diagnostics. The data is then classified either by a support vector machine (SVM), logistic regression (LR) or random forest. Accuracy and the F1-score are used as performance metrics. Of the three evaluated machine learning classifiers, LR has shown a slightly better performance than the others. PSD has proven to be more reliable than simple spectrograms. This work also utilizes the DroneRF data set [6]. To research the influence of interference on their approach, the authors also created their own data set (DroneDetect_V2, see section 3 for further details) and re-evaluated their approach with minor changes [10]. The authors, again use the pre-trained VGG16 CNN for feature extraction. Then classification is done by LR and k-nearest neighbor (KNN) respectively, with LR showing a better performance.

In contrast to the previously mentioned approaches, O'Shea et al directly use a raw IQ data stream as input for the ML algorithm [11]. A data set with IQ data from 11 different modulation schemes is recorded with a software defined radio (SDR). The complex IQ data is then directly used as input for a CNN. The used data set is available for free download. The results of the presented work are comparable to other expert feature based modulation classifiers. The work proposed in this paper picks up this approach and applies it to the classification of UAV signals.

3 Data Set

Allahham et al. created the DroneRF dataset [6], which is used in several works [7][8][9]. It is available to download for free and contains RF recordings from three drones in different flight modes. It's recorded with Universal Software Radio Peripheral (USRP) SDR transceivers. However, it contains only time series data and not complex IQ signals, making it unsuitable for the approach shown in this paper.

The DroneDetect_V2 data set, which is created by Swinney and Woods [10] is also available for free download at the IEEEDataPort. This data set contains raw IQ data captured with a BladeRF SDR. The samples are recorded with a sample rate of 60 Mbit/s at a center frequency of 2.4375 GHz. The data set contains recordings from seven drone models (six different DJI models and a Parrot Disco). Recordings are made in three different flight modes (switched on, hovering and flying). In *ON* mode, the drones are switched on but are not airborne. The distance between antenna and drone is 4 m. Additionally, the measurements are repeated with various types of radio interference. The interference modes are *CLEAN* (no interference), *BLUETOOTH* (interference created by a Bluetooth speaker), *WIFI* (created by personal WiFi hotspot from an Apple MacBook, used for video streaming) and *BOTH* (with simultaneous Bluetooth and WiFi interference). Unfortunately, some files (such as DJI Phantom in flying mode without interference) seem to be missing from the downloadable data set. It also doesn't contain any measurements without drones, which would be required for the evaluation of a drone detection (drone / no-drone classification).

For this reason, the downloaded data set is augmented with two types of self created noise samples. Thus allowing to evaluate the UAV detection capability of the proposed approach. The first type is ideal additive white Gaussian noise (AWGN), which is created with GNU Radio. The second type is SDR recorded background noise from an office / laboratory environment. The recordings are made with a USRP X310. The sample rate and center frequency are set to match the parameters, which are used to create the original data set. The IQ streams are written into individual files with the same size as the original drone recordings.

For the evaluation of the proposed approach, a subset of the recordings from the DroneDetect_V2 data set is used. Data from all seven drone models is used. Samples from flying mode are disregarded due to the missing data from the DJI Phantom 4. The Parot Disco is a flying wing type design and thus allows no hovering. Hence, only samples in *ON* mode are used. For the results presented in the next section, only samples without interference are taken into account. Thus, 35 files (five for each of the seven drones) of the DroneDetect_V2 data set are used. This is augmented witch five files of AWGN and SDR background noise recordings respectively, bringing the total to 49 files. From each file, the same number of IQ windows is picked at random spots within the file. Each of these IQ windows consists of 128 consecutive complex IQ samples. They are normalized according to the following equation,

$$x_{\text{norm}} = \frac{x - \bar{x}}{\sqrt{\text{Var}(x)}}, \tag{1}$$

where x represents the IQ samples. This follows the suggestion of the data set creators. The randomly normalized IQ windows, which are selected from 49 individual files, are then written into a single HDF5 files that also contains information on the classification, as well as, any relevant meta data.

4 Approach

The work presented in this paper follows the approach, which is presented by O'Shea et al [11]. A CNN is used to classify windowed samples of a raw IQ data stream. Instead of classifying the modulation scheme, the neural network is used for drone detection and classification of the drone type.

The CNN proposed in [11] is used with some small modifications (e. g. to adjust for the changed formatting of the input data). However, the overall layout of the original CNN remains unchanged. The model uses two convolutional layer (Conv2D), with a size of 64x2x2 and 32x2x1 respectively. The model also uses two dense layers, with 128 and 9 output neurons respectively. A rectified linear unit (ReLU) is used as activation function for all of these layers, except the second dense layer, where a softmax activation function is used instead. Besides this, the model has several zero padding and dropout layers. The CNN is setup with nine output classes, one for each of the seven drone types, one for AWGN and one for SDR background noise. Hence, the system performs UAV detection and classification tasks in one single run. A simplified illustration of the CNN's architecture is shown in Fig. 1.

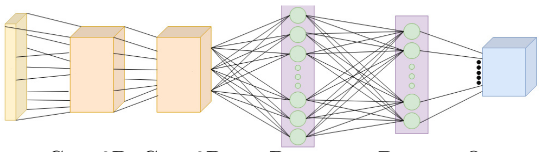

Figure 1. Simplified structure of the used CNN

The CNN is implemented using Keras and Tensorflow, running in an Docker environment on a graphics processing unit (GPU) server. For training and evaluation of the CNN, the augmented DroneDetect_V2 data set, as discussed in the previous section is used. The metrics for performance evaluation of the drone detection are defined as

$$\text{Accuracy} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N}, \tag{2}$$

$$\text{Precision} = \frac{T_P}{T_P + F_P}, \tag{3}$$

$$\text{Recall} = \frac{T_P}{T_P + F_N}, \tag{4}$$

$$F_1\text{score} = 2\left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\right), \tag{5}$$

where T_P, T_N, F_P, F_N represent true positive, true negative, false positive and false negative respectively [5].

The data set used for training and evaluation contains a total of 4,500,000 IQ windows. These are evenly distributed, with 500,000 in each of the nine classes. The data is evaluated using 5-fold cross validation.

5 Results

The results of the presented approach are presented in two separate steps, for UAV detection and classification, respectively.

5.1 Drone Detection

The goal of a drone detection system is to alert it's user to the presence of UAVs, by generating an alarm once a drone is detected. Hence, drone detection is a binary problem (i. e. "drone" or "no drone"). In contrast to this, the used CNN provides nine output classes. However, for the detection it makes no difference, which individual drone type a sample belongs to. Thus, the seven individual drone type classes can be combined into a single *ALARM* class. Similarly the two noise classes are combined into single *NO_ALARM* class. Using this approach and applying it to the equations 2 through 5, the following values can be obtained.

- **Accuracy: 99.41 %** This value provides information on the overall fraction of correctly classified samples.
- **Precision: 99.61 %** This value (also known as positive predictive value) states the fraction of the relevant instances among all retrieved instances. Each time a detection system classifies a sample as drone it generates an alarm. The precision value states the fraction of the alarms, which were correct. In turn, it also allows to quantize the fals alarm rate. Of the 3,499,542 alarms the CNN created, 3,486,525 were correct. In 13,017 cases the system generated a false alarm.
- **Recall: 99.63 %** This values (also known as sensitivity) states the fraction of relevant instances the system did retrieve. In this case it gives the fraction of how many of the 'incoming' drones the detection system was able to detect and how many it did miss. In total the CNN was presented 3,500,000 samples stemming from drones. 3,486,525 of these were classified correctly classified as drone and 13.475 were missed.
- **F1-Score: 99.62 %** This value is defined as the harmonic mean of precision and recall. It's a common metric to evaluate performance of a ML model.

5.2 Drone classification

The goal of drone classification is not only to know, when a UAV is present, but also which type it is. Hence, all nine output classes of the CNN are relevant in this case. In Fig. 2 the confusion matrix is shown. The illustrated values are averaged over all five fold of the cross validation.

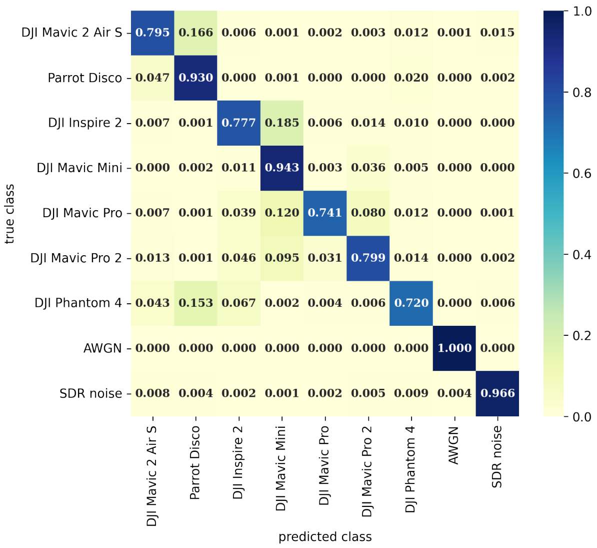

Figure 2. Overall confusion matrix

The achieved accuracy varies depending on the drone type. All values are in the range between 72 % and 94 %. The classification accuracy for the Parrot Disco and the DJI Mavic Mini are significantly higher, than for the other five drone types. The confusion matrix also shows, that CNN is 100 % reliable for the classification of ideal AWGN. For the SDR recorded background noise in a real-life office / laboratory environment, the system is a little less reliable, but still achieves a high accuracy of 97 %.

6 Future Work

The drone detection and classification results that are obtained with the proposed method of using a CNN as classifier for raw, windowed IQ data are satisfactory and show the feasibility of the approach. Especially, for drone detection, the CNN has performed quite well, with accuracy, precision and recall, all above 99 %. So far, only a subset (*ON* mode, without interference) of the DroneDetect_V2 data set has been used to evaluate this approach. In the next steps, flying modes and interference modes will also be considered. In the further course of the project it is planned to create RF recordings of various drone types in labratory and real-life conditions to further augment or replace the DroneDetect_V2 data set. With the proposed approach of directly processing IQ samples with a CNN, a direct integration into the GNU Radio flow graph of a SDR is feasible. For this a new GNU Radio signal processing block has to be written. This block could be loaded with the pre-trained CNN and then perform the classification on the live data stream from the SDR.

7 Acknowledgments

The work presented in this paper is part of the SIMULU project, which is funded by the German Federal Ministry for Digital and Transport. We also like to thank the authors of [10] and [11] for openly sharing their work, which is the basis for the presented approach.

References

[1] B. Taha and A. Shoufan, “Machine Learning-Based Drone Detection and Classification: State-of-the-Art in Research,” *IEEE Access*, vol. 7, pp. 138 669–138 682, Sep. 2019.

[2] Z. Shi, M. Huang, C. Zhao, L. Huang, X. Du, and Y. Zhao, “Detection of LSSUAV using hash fingerprint based SVDD,” in *2017 IEEE International Conference on Communications (ICC)*, Paris, France, 2017, pp. 1–5.

[3] P. Nguyen, M. Ravindranatha, A. Nguyen, R. Han, and T. Vu, “Investigating Cost-effective RF-based Detection of Drones,” in *DroNet ’16: Proceedings of the 2nd Workshop on Micro Aerial Vehicle Networks, Systems, and Applications for Civilian Use*, New York, USA, 2016, pp. 17–22.

[4] M. Ezuma, F. Erden, C. K. Anjinappa, O. Ozdemir, and I. Guvenc, “Micro-UAV Detection and Classification from RF Fingerprints Using Machine Learning Techniques,” in *2019 IEEE Aerospace Conference*, Big Sky, USA, 2019.

[5] O. O. Medaiyese, M. Ezuma, A. P. Lauf, and I. Guvenc, “Semi-supervised Learning Framework for UAV Detection,” in *2021 IEEE 32nd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, Helsinki, Finland, 2021, pp. 1185–1190.

[6] M. S. Allahham, M. F. Al-Sa’d, A. Al-Ali, A. Mohamed, T. Khattab, and A. Erbad, “DroneRF dataset: A dataset of drones for RF-based detection, classification and identification,” *Data in Brief*, vol. 26, p. 104 313, Oct. 2019.

[7] M. F. Al-Sa’d, A. Al-Ali, A. Mohamed, T. Khattab, and A. Erbad, “RF-based drone detection and identification using deep learning approaches: An initiative towards a large open source drone database,” *Future Generation Computer Systems*, vol. 100, pp. 86–97, Nov. 2019.

[8] Y. Zhang, “RF-based Drone Detection using Machine Learning,” in *2021 2nd International Conference on Computing and Data Science (CDS)*, Stanford, USA, 2021, pp. 425–428.

[9] C. J. Swinney and J. C. Woods, “Unmanned Aerial Vehicle Flight Mode Classification using Convolutional Neural Network and Transfer Learning,” in *2020 16th International Computer Engineering Conference (ICENCO)*, Cairo, Egypt, 2020, pp. 83–87.

[10] ——, “RF Detection and Classification of Unmanned Aerial Vehicles in Environments with Wireless Interference,” in *2021 International Conference on Unmanned Aircraft Systems (ICUAS)*, Athens, Greece, 2021, pp. 1494–1498.

[11] T. J. O’Shea, J. Corgan, and T. C. Clancy, “Convolutional Radio Modulation Recognition Networks,” in *Engineering Applications of Neural Networks*, Aberdeen, UK, 2016, pp. 213–226.