Classification of UAVsPresence, Type and Operation Mode Using Convolutional Neural Networks

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Abstract: The omnipresence of unmanned aerial vehicles (UAVs) in the civilian air space has led to their malicious usage raising high alert security issues. The countermeasures for detection and prevention of such activities are highly required. This work proposes aconvolutional neural network (CNN) to identify the flight modes of the UAVsfrom theremotely sensed radio frequency (RF) signatures. AnRF receiver is deployed to intercept the communication between the UAV and itsflight controller. Since deploying deep learning has witnessed the remarkable performance in almost every field of engineering and sciences, the proposed model comprises a neural network to identify the UAVs presence, its type and its operation mode. Furthermore, the considered flight modes of UAVsare classified into four categories:turned on and connected to its controller, hovering, flying without video recording, and flying with video recording. Finally, the performance of CNN is evaluated using various parameters of confusion matrix which confirms the viability of the proposed system.

Keywords.UAVs;UAV surveillance;convolutional neural network (CNN);flight modes; RF signatures

1. Introduction

An unmanned aerial vehicle(UAV)is an autonomous aircraft and is apart of the unmanned aerial system (UAS). UAS includes a UAV, a flight controller, and a communication link between them.Originally,UAVs were used for military applications in the missions difficult for humans, but nowadays they are rapidly outnumbered from military UAVs to civilian UAVs as the availability and affordability of commercial UAVs.Due to their small size, lightweight, huge mobility capabilities, andinnovative batteries and motors, the popularity of the commercial UAVs is rising day by day**(Kuru *et al.*,2019;Shakhatreh*et al.*,2019)**.Meanwhile, their applications are entering almost every job horizon, covering most scientific works, communication, commercial broadcasting, package delivery, aerial photography, agriculture, infrastructure inspection, advertising, traffic monitoring, live streaming,and many other such applications.However, there are a lot of possibilities to misuse UAVs that are considered unethical, such as spying, cyber-attacks, smuggling payloads, trespassing, filming people without permission, etc.**(Kuru *et al.*,2019;Shakhatreh*et al.*,2019;Alsamhi*et al.* 2019)**. For instance, in one case a person operatinga UAV in a restricted airspace was arrested during a protest in July 2020 **(Fox News 2020)**, and in another case aUAV had entered theWhite House premises in Washington DC in January 2015**(BBC 2015)**. Hence, the predictability of the suspectedUAVs has become a major issueas there have been ample irregularities caused by the UAVs. These unethical activities are prevailing abundantly around the globe**(Shakhatreh*et al.*,2019; Alsamhi*et al.*,2019;Moses *et al.*,2011)**. In this regard, various issues related to technical, security, and safety need to be carefully addressed by the regulatory authorities for the ubiquitous utility of UAVs in private airspace. Therefore, the regulatory authorities are keen to find the solution of detection and identification of working modes ofUAVs, and itmotivated this research work.

1.1. Related Works

A lot of research work is undergoing for detection and identificationof UAVsto prevent their misusage.Through doppler signatures, a radar system was deployed by **(Moses *et al.*,2011)**andbased on the same,a system for 5G millimeter wave (mmWave)was exploited by **(Solomitckii*et al.*,2018)**for the detection of UAVs.Furthermore, in **(Chang*et al.*,2018)**detection and tracking of UAVs were performed by estimatingthe direction of arrival using acoustic cameras. The authors of **(Bisio*et al.*,2018)**designed energy efficient UAV detection system on the basis of wireless fidelity (Wi-Fi)UAV signatures.However, a radio frequency (RF) based UAV detection system presented in**(Nguyen*et al.*,2016)**was cost-effective, easily deployable,and functional in all weather conditions due to RF signal usage. The authors in **(Güvenç*et al.*,2018; Azari*et al.*,2018)**reviewed the various adopted methodologies for detecting and tracking the interfering UAVs. They determined that RF-based UAV detection systems are more suitable for practical scenarios among all the UAV detection systems. The characteristic features of RF signals,such as penetration through most of the obstacles, large coverage distance, cheaper equipment cost, etc. makes it ideal for the usage in the UAV detection system. Moreover, RF sensing is impartialto the communication technology, e.g. Wi-Fi, Bluetooth, 4G, or 5G etc.used by UAVs to communicate with theirflight controllers**(Azari*et al.*,2018)**.

For developing an intelligent RF-based UAVdetection system,a deep neural network (DNN) was integrated to extract the full capability of the system. In previous works, deep learning (DL) based UAV detection systems were developed from doppler signatures in **(Mendis*et al.*,2018;Kim*et al.*,2017)**and from surveillance videos in **(Shijith*et al.*,2017)**. Moreover, RF-based UAV detection and identification system was developed using DNN by the authors of**(Al-Sa'd*et al.* 2019)** after generating their own RF database of various UAVs under different flight modes. Along with the detection of UAVs, it is also essential to predict UAV activitiestofurther classifying the restricting zones for UAVs according to their permitted or denied usagesof that zone.

1.2. Contributions

Based on the prior studies, this paper proposes a two-, four- and ten- class classifier convolutional neural network (CNN) model integrated to detect UAV, predict its type and its modes of operation from RF signaturesfor continuous monitoring. These RF signatures are captured by a receiver known as RF sensing module that eavesdrops the communication between the UAV and itsflight control module.An open-source database of RF signatures is used in this work which was developed by**(Al-Sa'd*et al.* 2019)**.This database has the RF signatures that werecapturedfrom various UAVsvia RF sensing module (NI-USRP 2943R). Through this database, the designed two-, four- and ten- class classifier CNN modelis trained.As, during the training phase CNN learns about the classes, and the RF signatures intercepted from the UAV under analysis are tested on trained CNN and afterwards,the detection,identification and operation mode of the UAVis realized.

The rest of the paper is organized as follows: The system model is presented in section 2 with the details on the signal preprocessing stage, and CNN architecture. Simulation results in the form of a confusion matrix are presented in section 3. Lastly, section 4 concludes this work along with its future scope.

2. System Model

The considered system model shown in figure 1 comprises two subsystems: 1) network between UAV and flight control module, and 2) network of RF sensing module connected with UAVtwo-, four- and ten- class classifierCNN. The open-source database of RF signatures used in this work for conducting training and testing of CNN was developed by a community of researchers in**(Al-Sa'd*et al.* 2019)**. In this work,the exploited RF database was sensed by RF sensing module NI-USRP 2943R for (a) Parrot Bebop, (b) Parrot AR 2.0 elite edition and (c) DJI Phantom 3 UAVillustrated in figure 2. The RF signatures were recorded for four flight modes of UAVfor Parrot Bepop and Parrot AR 2.0 listed as 1) turned on and connected to its controller, 2) hovering, 3) flying without video recording, and 4) flying with video recording and a single mode of operation, i.e., turned on and connected to its controller for DJI Phantom 3 UAV. The details ofwhole system are discussed further in subsequent two subsections.

2.1. Signal Preprocessing

Firstly, preprocessing of the obtained signal from RF sensing module isimplemented. Specifically,RF sensing module NI-USRP 2943R used in **(Al-Sa'd*et al.* 2019)**is capable to capture the signal of 40MHz bandwidth only, whereas, generally usedRF spectrum is of about 80MHz. Therefore, two RF receivers were employed in **(Al-Sa'd*et al.* 2019)**to capture the full spectrum of RF signature, where the first one recorded lower half of the spectrum $x_i^{(L)}$and the second one recorded upper half of the spectrum $x_i^{(H)}$. The ith segment of RF signature having $n \in (1, \dots, N)$ time domain indices need to be converted into $m \in (1, \dots, M)$ frequency domain indices for extracting the relevant information used for the classification by CNN as illustrated in figure 3. Thus, for obtaining frequency spectra DFTs of the signalsreceived from both receivers $x_i^{(L)}$ and $x_i^{(H)}$ are computed in signal preprocessing block and are given by $y_i^{(L)}$ and $y_i^{(H)}$respectively.

$$y_i^{(L)}(m) = \left\| \sum_{n=1}^{N} x_i^{(L)}(n) \exp\left(-\frac{j2\pi m(n-1)}{N}\right) \right\| \tag{1}$$

$$y_i^{(H)}(m) = \left\| \sum_{n=1}^{N} x_i^{(H)}(n) \exp\left(-\frac{j2\pi m(n-1)}{N}\right) \right\| \tag{2}$$

Figure 1 System model for signal acquisition, preprocessing and feeding to CNN for learning.

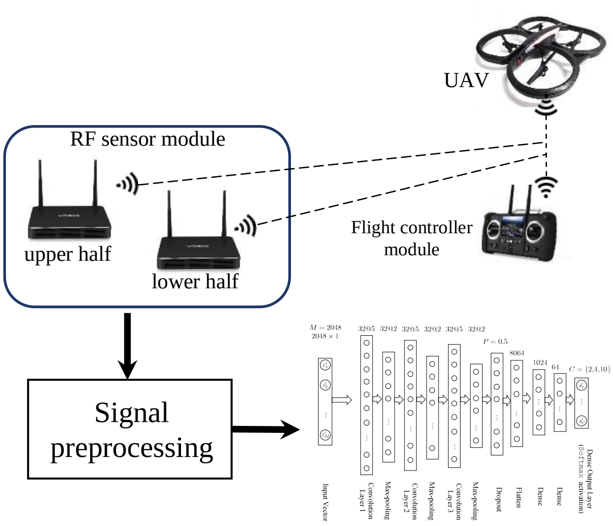


Figure 2 The actual representation of the UAVs under consideration (a) Parrot Bebop UAV, (b) Parrot AR 2.0 elite edition UAV, and (c) DJI Phantom 3 UAV**(Al-Sa'd*et al.* 2019)**

(a) (b) (c)

These transformed signals of both receivers are further concatenated to obtain the entire RF spectrum $y_i(m)$as follows:

$$y_i(m) = \left[y_i^{(L)}(m),\ c\, y_i^{(H)}(m)\right] \tag{3}$$

$$c = \frac{\sum_{q=0}^{Q} y_i^{(L)}(M-q)}{\sum_{q=0}^{Q} y_i^{(H)}(q)} \tag{4}$$

where, c is the ratio of last Qelements of $y_i^{(L)}(m)$ to first Qelements of $y_i^{(H)}(m)$, and M is the total number of intervals in the RF spectrum $y_i(m)$.

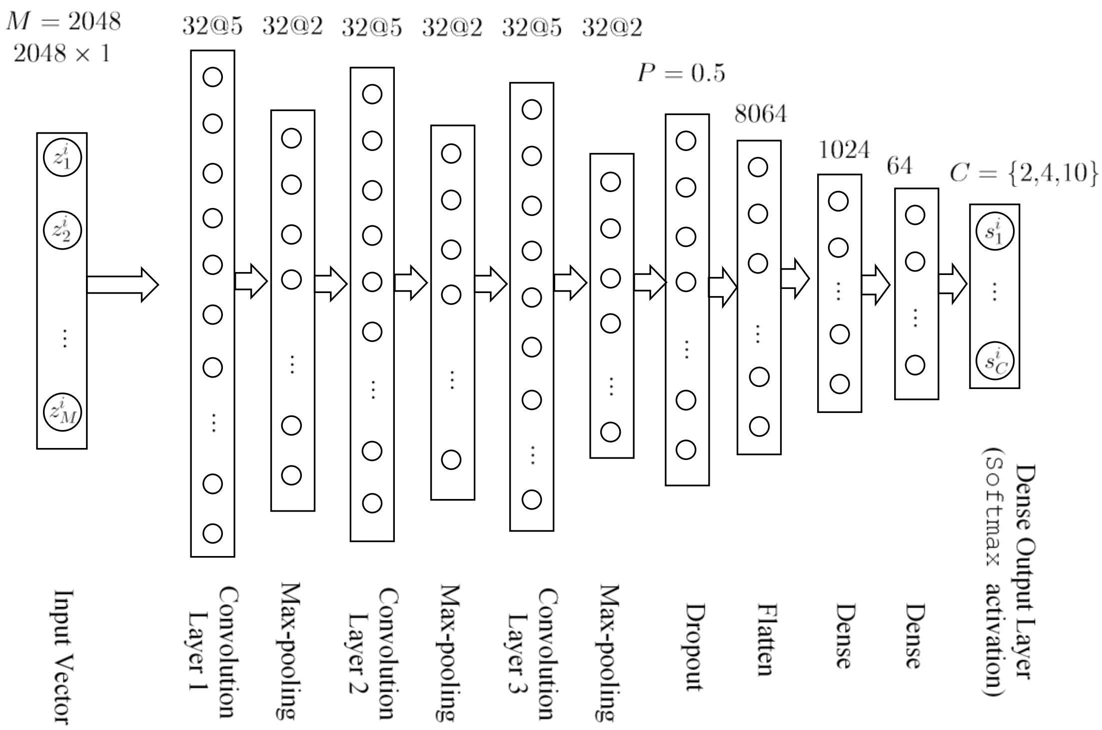
Lastly, the normalization of the signal $z_i(m)$is computed at the preprocessing stage using (5) which is given by

$$z_i(m) = \frac{y_i(m)}{\sum_{j=1}^{M} y_i(j)} \tag{5}$$

2.2. CNN Architecture

The proposed system architecture as illustrated in figure 3 consists of a CNN having `'softmax'` classifier layer as the output. The preprocessed RF signatures $\boldsymbol{z}_i = [z_i(1), z_i(2), \dots, z_i(M)]'$are fed to CNN for training and testing. Overall, the CNN comprises of various fully connected 1D convolutional layers (`Conv1D`) with 32 filters,kernel size of 5 and their activation function as Rectified linear layer (`ReLU`). Each `Conv1D`layer is followed by a `MaxPooling1D` layer with a pool size of 2. This network of `Conv1D` and `MaxPooling1D` is followed by the `Dropout` layer with a rate of `0.5`, to prevent overfitting of the network during training process. Then is the `Flatten` to convert the data into an array form, and lastly there a couple of `Dense` layers with activation function as `ReLU`to match the data to the number of classes.The output layer classifies output into R classes with the use of `'softmax'` classifier. The detailed information about the number of layers, dimension, output parameters and activation functions is provided in Table 1

Figure 3 Layer wise system architecture of proposed CNN classifier



3. Simulation Results

The 10^7RF signatures for each flight modeof 227 datasets for lower frequency spectrum and 227datasets for higherfrequency spectrum are obtained from **(Al-Sa'd*et al.* 2019)**. Further,the segmentation by a factor of 100on the above database is performed for better learning. The resultant instantaneous RF signal representation comes to $N = 10^5$. For each RF segment, FFT is performed with 2048 frequency bins ($M = 2048$). The entire RF spectrum is then reconstructed from its lower and upper half of the spectra using equation (3). Out of 22700 segments, 20430 are employed for training and 2270 are employed for testing. The number of epochs and batch size considered are 1000 and 256, respectively. The performance evaluation of CNN is shown in figure 4 using the confusion matrix which estimates the efficiency of variousclassifiers.The rows and columns of the confusion matrix with the matricesrepresent the output(predicted) and target (actual) classes, respectivelyforpresence and absence (two-class), type of UAV (four-class) and type withmode of operation (ten-class). The diagonal bold elements correspond to the segments that are rightly classified and off-diagonal elements correspond to the segments that are wrongly classified. The performance of the flight mode identification system can be evaluated using various confusion metrics,such as accuracy, recall, precision, false discovery rate (FDR), false negative rate (FNR), error, etc. The formulation of these performance metrics is given below:

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

$$\text{recall} = \frac{TP}{TP + FN} \tag{7}$$

$$\text{precision} = \frac{TP}{TP + FP} \tag{8}$$

$$FDR = 1 - \text{precision} \tag{9}$$

$$FNR = 1 - \text{recall} \tag{10}$$

$$\text{error} = 1 - \text{accuracy} \tag{11}$$

where, $TP, TN, FP,$ and FN are true positives, true negatives, false positives, and false negatives, respectively.$TP$for a class is the bold value that is formed by the intersection of predicted and actual classes, TN is the sum of all rows and columnsin the matrix except the predicted rows and actual columns.$FP$is sum of all the elements from the predicted row except TP, whereas FN is sum of all the elements from the actual row except TP.The various modes of operation of the UAVs are as follows:

Mode 1. Turned on and connected to its controller
Mode 2. Hovering
Mode 3. Flying without video recording
Mode 4. Flying with video recording

Parrot Bepop and Parrot AR 2.0 UAVs are considered operating in all the four mentioned modes while the third UAV, i.e., DJI Phantom's operation is considered restricted to mode 1.

Table 1 Representation of performance parameters of a ten-class CNN classifier based on confusion matrix

Performance Parameter	**UAV Absent**	**Bebop Mode 1**	**Bebop Mode 2**	**Bebop Mode 3**	**Bebop Mode 4**	**AR Mode 1**	**AR Mode 2**	**AR Mode 3**	**AR Mode 4**	**Phantom Mode 1**
recall	1.00	0.82	0.57	0.19	0.45	0.55	0.35	0.35	0.64	0.83
accuracy	1.00	0.93	0.91	0.76	0.91	0.91	0.90	0.84	0.92	0.96
precision	1.00	0.33	0.48	0.52	0.21	0.37	0.10	0.70	0.35	0.65
FDR	0.00	0.67	0.52	0.48	0.80	0.63	0.90	0.30	0.65	0.35
FNR	0.00	0.18	0.43	0.81	0.55	0.45	0.65	0.65	0.36	0.17
error	0.00	0.07	0.09	0.24	0.09	0.09	0.10	0.16	0.08	0.04

Table 2 Description of layers of the proposed two-, four- and ten-class CNN classifier

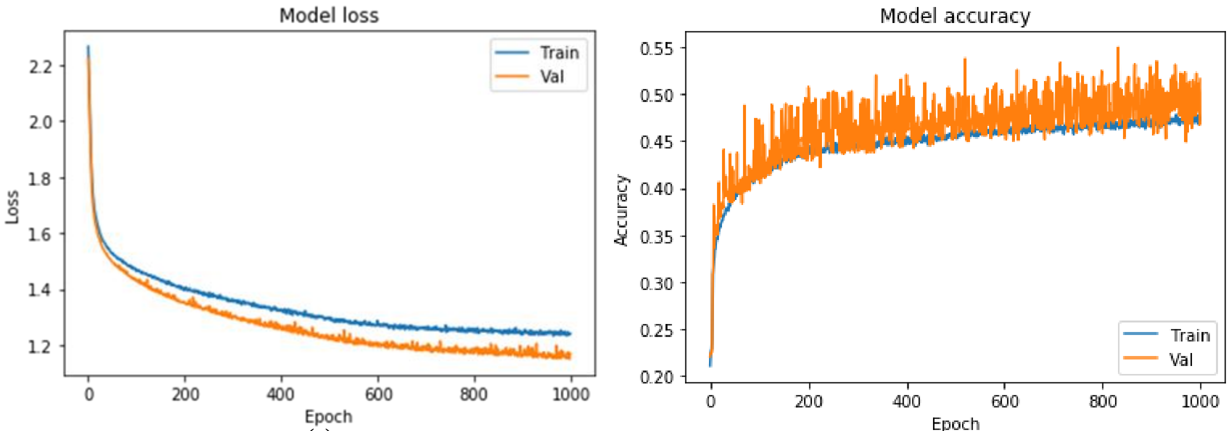
Layer name	**Output dimension**	**Activation function**	**Number of parameters**

Input	2048×1	-	-
Conv1D	2043×32	relu	192
Max-pooling	1021×32	−	0
Conv1D	1017×32	relu	5152
Max-pooling	508×32	−	0
Conv1D	504×32	relu	5152
Max-pooling	252×32	−	0
Dropout $(\mathbf{0.5})$	252×32	−	0
Flatten	8064	−	0
Dense	1024		8258560
Dense	64		65600
Dense (output)	$\{2,4,10\}$	SoftMax	$\{130, 260, 650\}$

For two-class classification by the proposed CNN classifier, the model performs ideally, as it can be deduced from figure 6(a) that the number of predicted and actual classes are same and the accuracy of each class is a 100%. While in case of four-class classification figure 6(b) and ten-class classification figure 7 the results deviate from the values of TP of confusion matrix in the cases where UAV is present, while in both cases of four- and ten-class classification the identification of the RF signal where UAV is absent gives a 100% accuracy. The depictions of various UAVs in a four-class classification becomes a bit difficult for the proposed classifier as the RF signals intercepted from various UAVs have similar frequency characteristics, so the overall accuracy of the system falls from 100% form two-class to 88.37% for four-class classifier. The overall system classification accuracy becomes worse in a ten-class classification, as in this case the UAV's mode of operation is also included in the CNN classification task along with the detection of presence, as well as detecting the type of UAV. But if a comparison is made with the model proposed by **(Al-Sa'd*et al.* 2019)**, the present works shows the improvement from 46.8% to 52.11% in ten-class classification process. This scenario is also visible in case of two- and four-class classification in the proposed model as the accuracy of the model for two-class classification has been improved from 99.7% to 100%, while an improvement from 84.4% to 88.37% has been achieved by the four-class classifier.

So, it can be figured out that by choosing the above-mentioned number of neurons of the layers, batch size and epochs, proposed CNNclassifier leads to overall system accuracy of 100%, 88.37% and 52.11% for two-, four- and ten-class classifiers respectively. And shows a significant improvement form the model presented by **(Al-Sa'd*et al.* 2019)**.The higher value of diagonal elements of confusion matrix indicates better predictions by CNN and can be further improvised by using advanced classification algorithms in CNN.

Figure 4 Accuracy and loss of the proposed ten-class CNN classifier in training phase



(a) (b)

Figure 5 Confusion matrices for proposed CNN classifiers showing the presence and absence of UAV in (a) two-class classifier and the type of UAV in (b) four-class classifier.

	UAV Absent	UAV Present	Predicted
UAV Absent	**448**	0	448
UAV Present	0	**1822**	1822
Actual	448	1822	**2270**

(a)

(b) →

	UAV Absent	Bebop	AR	Phantom	Predicted
UAV Absent	**397**	0	0	0	397
Bebop	0	**790**	34	0	824
AR	0	147	**671**	19	837
Phantom	0	1	63	**148**	212
Actual	397	938	768	167	**2270**

Figure 6 Confusion matrix for proposed ten-class CNN classifier showing the mode of operation of different UAVs

	UAV Absent	Bebop Mode 1	Bebop Mode 2	Bebop Mode 3	Bebop Mode 4	AR Mode 1	AR Mode 2	AR Mode 3	AR Mode 4	Phantom Mode 1	Predicted
UAV Absent	419	0	0	0	0	0	0	0	0	0	419
Bebop Mode 1	0	75	2	131	1	18	0	0	0	0	227
Bebop Mode 2	0	0	108	98	2	6	1	12	0	0	227
Bebop Mode 3	0	6	38	109	46	3	0	7	0	0	209
Bebop Mode 4	0	8	3	142	41	5	0	1	0	0	200
AR Mode 1	0	3	35	79	1	78	1	14	0	0	211
AR Mode 2	0	0	2	0	0	2	19	130	21	14	188
AR Mode 3	0	0	1	0	0	26	12	137	17	2	195
AR Mode 4	0	0	0	0	0	4	21	91	67	10	193
Phantom Mode 1	0	1	0	0	1	4	13	44	8	130	201
Actual	419	93	189	559	92	146	67	436	113	156	2270

4. Conclusion

The popularity of UAVs among civilians has raised alarming security concerns regarding their usage. This work encompasses training of CNN withRF signatures of UAVs for presence, type and mode of operation of UAV. This trained CNN isemployed for prediction ofUAV using unknown RF signatures intercepted from the UAV.The future scope of this work could be the fusion of the classified RF signatures according to their flight modes with other UAVmodalities, such as camera images or videos, radar or acoustic echoes, etc. The effect of RF interferences while intercepting the RF signatures from the UAVs can also be modeled for designing the practicalUAVidentification system.This work can also be extended to any number of flight modes by acquiring their datasets accordingly.

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