Radar-based Drone Detection using Complex-Valued Convolutional Neural Network

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2023 IEEE Sensors Applications Symposium (SAS) | 979-8-3503-2307-8/23/$31.00 ©2023 IEEE | DOI: 10.1109/SAS58821.2023.10254135

***Abstract*—With an unprecedented growth in the number of commercially available drones, the detection of drones is becoming increasingly essential. Deep learning-based convolutional neural network (CNN) models utilizing micro-Doppler signatures, are being widely used for drone detection applications. Radar returns from a drone and its corresponding micro-Doppler signatures are often complex-valued. However, the CNNs only consider the magnitude component of the micro-Doppler signatures while ignoring the phase component. This phase component contains essential information that can supplement the magnitude for enhanced drone detection. Thus, this paper proposes a novel complex-valued CNN that considers the magnitude and phase component of the radar returns. This paper also investigates the performance of the proposed model with radar returns of different sampling frequency and duration. A comparative analysis of the performance of the proposed model in the presence of noise is also presented. The proposed complex-valued CNN model achieved the highest detection accuracy of 93.80% when the radar returns were sampled at 16000 Hz and for duration of 0.01s. This shows that the proposed model can successfully detect drones that appear in the radar for an extremely short interval of time.**

***Index Terms*—Drone detection, radar time series, Spectrograms, HERM lines, complex-valued CNN.**

I. INTRODUCTION

With an increasing number of commercially available drones and their widespread proliferating applications, drone detection and classification are crucial for preserving public safety. Drone detection and classification using acoustic sensors [1] or optical sensors [2] have been explored. However, the range of both the sensors are very limited. Acoustic sensors are highly perceptible to environmental noise while optical sensors are weather-sensitive. Radars, on the other hand, have a relatively longer range of detection and perform equally well under all weather conditions. Thus, radars have been widely used for drone detection and classification [3]. Drone detection and classification can be defined in their strict sense. Drone detection refers to detecting the presence of a drone while drone classification refers to identification of the type of drone after detection. This work focuses on radar-based drone detection application only.

Deep learning and machine learning have proven to be highly efficient in drone detection [4], [5]. The micro-Doppler signatures or spectrograms of radar returns from a drone have been used to detect drones [6]. These signatures contain information of the periodic motion of drone propellers/blades which help in distinguishing between a radar return from a drone and noise. Radar returns are complex-valued signals that produce complex-valued spectrograms, containing both magnitude and phase information. Majority of state-of-the-art works consider only the magnitude component of the complex-valued spectrograms for drone detection [7] , [8] and the phase component is discarded. However, this phase component contains significant information that may supplement the magnitude information for improved drone detection and classification [9]. Thus, this work proposes a novel complex-valued convolutional neural network (CNN) model for drone detection.

In this work, the radar returns of popular commercially available drones have been simulated using the Martin-Mulgrew (MM) model [10] and these simulated complex-valued time series have been used for binary classification. These radar returns have been modelled at different signal-to-noise ratios (SNR) (5dB, 10dB and 15dB) for extensive model performance analysis in the presence of noise. The contributions of this work are:

- Two new complex-valued CNN models have been proposed with complex-valued time series and complex-valued spectrograms as inputs individually. A third real-valued CNN model has also been presented to compare the performances.
- An exhaustive comparative analysis of the performances of these three CNN models has been carried out on three datasets corresponding to different sampling frequency

and signal duration. For each of these three simulated datasets, the classification has been performed with three different SNRs (5dB, 10dB and 15dB).
- The execution time of the proposed models has also been explored.

The remainder of this paper is organized as follows. Section II discusses the dataset generation and data pre-processing procedures. Section III introduces the proposed experimental model while Section IV shows the results and the inferences that can be drawn. Section V concludes the paper.

II. Data Preparation

A. Data generation using Martin-Mulgrew Model

The Martin-Mulgrew (MM) model [10], originally designed to analyse the radar returns of aircraft propeller blades, can model radar return signals (in form of complex times series of desired time duration) of any aerial object with rotating propellers such as drones. This MM model is given as:

$$\Psi(t) = A_r e^{j\left(2\pi f_c t - \frac{4\pi}{\lambda}(R+V_{rad}t)\right)} \sum_{n=0}^{N-1} \left(\alpha + \beta\cos\left(\Omega_n\right)\right) e^{-j\frac{L_1+L_2}{2}\gamma_n} \operatorname{sinc}\left(\frac{L_2-L_1}{2}\gamma_n\right)$$

where

$$\begin{aligned} \alpha &= \sin\left(|\theta| + \Phi_p\right) + \sin\left(|\theta| - \Phi_p\right) \\ \beta &= \operatorname{sign}(\theta)\left(\sin\left(|\theta| + \Phi_p\right) - \sin\left(|\theta| - \Phi_p\right)\right) \\ \Omega_n &= 2\pi\left(f_{rot}t + \frac{n}{N}\right) \\ \gamma_n &= \frac{4\pi}{\lambda}\cos(\theta)\sin\left(\Omega_n\right) \end{aligned} \tag{1}$$

A_r is a real, scaling factor,
L_1 is the distance of the blade roots from the centre of rotation,
L_2 is the distance of the blade tips from the center of rotation,
N is the number of blades,
R is the range of the target,
V_{rad} is the radial velocity of the center of rotation with respect to the radar,
λ is the wavelength of the transmitted radar signal,
θ is the angle between the plane of rotation and the line of sight from the radar to the center of rotation,
f_c is the frequency of the transmitted radar signal,
f_{rot} is the frequency of rotation of drone blades,
t is the time duration of radar returns,
Φ_p is the pitch of the blades

The simulation parameters N, L_1, L_2, and f_{rot} characterises drone blades/propellers while λ and f_c determine the type of radar. The position of the drone relative to the radar is defined by θ, Φ_p, R and V_{rad}. The data generated using the MM model is discretized at a sampling frequency of f_s.

In this work, radar returns of an X-band radar from 5 different types of commercially available drones (DJI Mavic Air 2, DJI Mavic Mini, DJI Matrice 300 RTK, DJI Phantom 4 and Parrot Disco) are simulated using the MM model. The simulated X-band radar has a wavelength λ of 3cm, transmitting frequency f_c of 10 GHz and pulse repetition frequency (PRF) of 2kHz. The approximate drone parameters of each drone for which the radar returns are simulated are shown in Table I.

TABLE I
Approximate drone-blade parameters of drones.

Drone type	N	L_1 (cm)	L_2 (cm)	f_{rot} (Hz)
DJI Mavic Air 2 [7]	2	0.50	7.00	91.66
DJI Mavic Mini [7]	2	0.50	3.50	160.00
DJI Matrice 300 RTK [7]	2	5.00	26.65	70.00
DJI Phantom 4 [7]	2	0.60	5.00	116.00
Parrot Disco [7]	2	1.00	10.40	40.00

The drones shown in Table I have fixed blade pitches. However, several commercially available drones have variable blade pitches, thus, to maintain generalizability, Φ_p, θ and R are considered as variable parameters that are uniformly distributed in the range of $\left(0, \frac{\pi}{4}\right)$, $\left(\frac{\pi}{16}, \frac{\pi}{2}\right)$ and $(500, 2000)$ respectively [4]. The radial velocity of the drone V_{rad} is kept constant at 4 rad/s. Each radar return from a drone is polluted with a complex-valued Gaussian noise of a particular SNR which determines the scaling factor A_r according to the following equation:

$$\mathrm{SNR} = 10\log_{10}\left(\frac{A_r^2}{\sigma^2}\right) \tag{2}$$

where σ^2 is the variance of the added Gaussian noise and is equal to 1 in our simulations (Note: the mean of the added Gaussian noise is 0). Therefore, for a given SNR, A_r is given as:

$$A_r = 10^{\mathrm{SNR}/20} \tag{3}$$

In this work, three different datasets of different signal duration t and sampling frequency have been simulated. The total number of samples in each radar return has been kept fixed (equal to 160 samples) as shown in Table II. Each dataset contains 2000 time series (samples) of each of the five drone classes and 10000 complex valued Gaussian noise signals of the same duration t. Each dataset has radar returns polluted with Gaussian noise of three different SNRs, 5dB, 10dB and 15dB individually. Thus, three variations of each dataset type at three different noise levels are simulated for analysis.

TABLE II
Types of dataset simulated.

Set	Signal Duration	Sampling Frequency	Total Samples
Set A	0.1s	1600Hz	160
Set B	0.05s	3200Hz	160
Set C	0.01s	16000Hz	160

B. Data pre-processing

The micro-Doppler signatures (or spectrograms) corresponding to the rotating blades of the drones enables its detection. The magnitude of the short-time Fourier transform (STFT) applied on the simulated complex radar-returns (complex time series) produces spectrograms. It can be given as:

$$X(m,\omega) = \left| \sum_{n=-\infty}^{\infty} x(n)w(n-m)e^{-j\omega n} \right|^2 \tag{4}$$

where $w(n)$ is the window function centered at time index m. To detect the drones accurately, the rotation period of drone blades should be observed in a spectrogram. This observation is dependent on the applied window size. If the window size is at least half the rotation period of the blades then a wideband spectrogram is formed showing the periodicity of the rotating blades over the entire time duration. This is called the blade flash phenomena [11]. However, to capture these blade flashes, either the radar PRF should be high or the applied window size should be longer than the period of blade rotation. Hardware implementation of a radar with high PRF is extremely difficult. Thus, a long window STFT can be used to capture blade flashes through HElicopter Rotation Modulation (HERM) lines [12].

In this work, long Hamming windowed STFT with 80% overlap has been used to produce spectrograms which serve as an input to the deep learning models described in Section III. The window size w is estimated based on the period of blade rotation of a drone and is given as:

$$w = \frac{f_s}{f_{rot}} \tag{5}$$

where f_s is the sampling frequency in KHz and f_{rot} is the frequency of the rotation of drone blades in Hz. The simulated radar return (with SNR 15dB) of Parrot disco drone and its corresponding short windowed STFT (window length of 128 samples) and long windowed STFT spectrograms (window length of 512 samples) is shown in Figure 1. The periodicity of rotating blades is clearly observed in the long-window STFT. The simulated Gaussian noise and its corresponding short windowed STFT and long windowed STFT spectrograms which does not show the periodicity of rotating blades is shown on Figure 2.

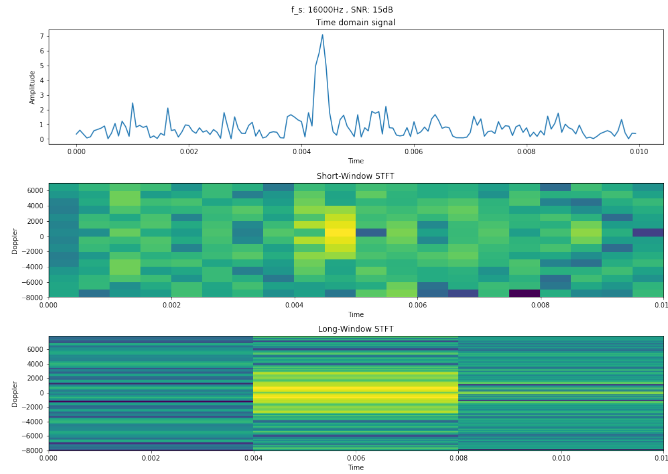

Fig. 1. STFT plots of Parrot Disco Drone

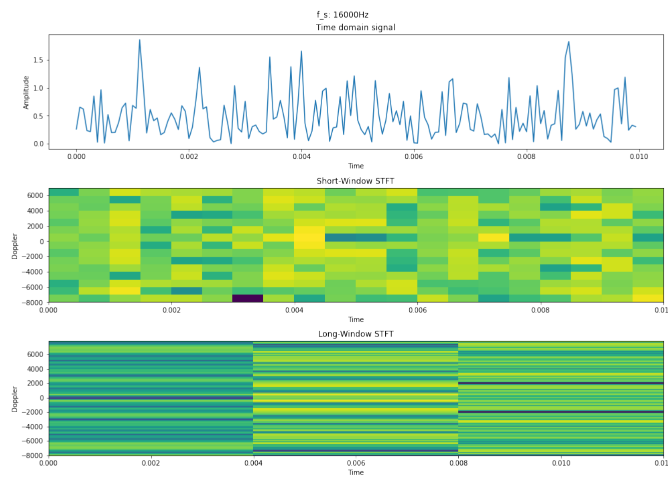

Fig. 2. STFT plots of Gaussian Noise

III. Experimental Approach

The majority of existing work uses the magnitude of the complex-valued radar returns for drone detection or other application. However, radar returns are complex-valued signals, having both magnitude and phase components. Thus, using both magnitude and phase components of the complex valued radar returns will provide more information that will facilitate better drone detection. This work presents an exhaustive comparative analysis of the performance of deep-learning complex-valued CNN models with different types of inputs. Three different types of inputs (both time and frequency domain inputs), namely, magnitude of spectrograms (real frequency domain input), magnitude and phase of spectrograms (complex frequency domain input) and raw radar returns (complex time domain input) have been analysed. Three different convolutional neural networks (CNN)-based deep-learning models have been introduced. Fig.3 shows pipeline of the proposed deep-learning models.

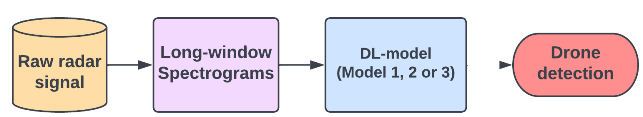

Fig. 3. Pipeline of the proposed deep-learning models

A. Model 1: Real-valued CNN on the magnitude of the spectrograms

In this model, magnitude of spectrograms are used as an input to a CNN-based model. The complex-valued radar returns are split into real and imaginary components and long-windowed STFT is applied on the real and imaginary components individually to obtain real-valued STFTs which are then concatenated to form a 2D-array. This 2D real-valued array serves as an input to a CNN-model made up of six blocks. Each block consists of a 2D convolutional layer followed by an instance normalization layer except the last block which does not contain an instance normalization layer. The first block was followed by a max pooling layer and each block is followed by a dropout layer of 0.5 probability. All blocks had leaky Rectified Linear Unit (ReLU) as activation function. The kernel size of the 2D convolutional layers in the first two blocks are 1×9 and 5×5, respectively, while the rest of 2D convolutional layers in each of the blocks has a kernel size of 3.

B. Model 2: Complex-valued CNN on the complex-valued spectrograms

In this model, complex-valued spectrograms are used as inputs to the complex-valued CNN-based model [13]. Long-windowed STFT is applied to the raw radar return which produces complex-valued STFTs. These STFTs are then used as inputs to a CNN-model made up of six blocks. Each block consists of a 2D convolutional layer followed by an instance normalization layer except the last block which does not contain an instance normalization layer. After the third block, the magnitude of the complex output of the third block is calculated and fed into the fourth block for further processing. The first three blocks have complex-valued 2D convolutional layers with complex leaky ReLU as activation function while the last three blocks have real-valued 2D convolutional layers with leaky ReLU as activation function. The first block was followed by a max pooling layer and each block is followed by a dropout layer of 0.5 probability. All 2D convolutional layers have a kernel size of 3×3.

C. Model 3: Complex-valued CNN on the raw complex radar time series

In this model, complex-valued raw radar returns (time series) are fed into a CNN-based model which also consists of six blocks. The first block consists of a complex 1D convolutional layer with kernel size 3×3 and complex ReLU activation function followed by an instance normalization layer. The output of the instance normalization layer is a complex 2D array which is then fed into the second block consisting of a complex 2D convolutional layer with kernel size 3×3 and complex leaky ReLU activation function followed by an instance normalization layer. The third block is similar to the second block and outputs a complex-valued 2D array. The magnitude of this complex array is calculated and fed into the fourth block of the CNN model that consists of a real-valued 2D convolutional layer with kernel size 3×3 and leaky ReLU activation function followed by instance normalization layer and a max pooling layer. The last two layers are made up of a real-valued 2D convolutional layer with kernel size 3×3 and leaky ReLU activation function followed by an instance normalization layer.

IV. Results and Discussions

In this work, drone detection has been posed as a classification problem with two classes, namely, 'Drone Present (DP)' and 'Drone Absent (DA)'. Each class has 10000 time series of sample length 160. The class DP has 2000 complex time series of five different types of drones to demonstrate the applicability of the proposed model irrespective of drone type. The class DA has 10000 complex Gaussian noise series, each of length 160. The input datasets were split into 80%-20% training and test dataset. A 5-fold cross validation technique was used for testing.

The proposed models were trained for 100 epochs with a learning rate of 0.001 and an early stopping function of patience 15. Adam optimizer and cross entropy loss function was used for all proposed models. The performance of the proposed models for drone detection is evaluated using several performance metrics such as accuracy, precision, recall and F1-score. The performance metrics of the proposed models with various sets of input signals of different signal duration, sampling frequency and level of noise is shown in Table III. An SNR of 5dB refers to a high level of noise present while an SNR of 15dB implies a low level of noise. The total number of samples is kept equal to 160 for all complex time series.

The simulated time series in set A has the longest signal duration and lowest sampling frequency whereas the simulated time series in set C has the shortest time duration and highest sampling frequency as shown in Table II. The following observations can be made from Table III:

- The performance of each of the proposed models decreases when the SNR decreases: the performance of the models at SNR 15dB is better as compared to the performance of the models at SNR 5dB.
- The performance of models with Set C inputs is significantly higher when compared to the performance of the models with Set B and Set A inputs at all SNR levels. The performance of models with Set A inputs is the lowest. This implies that the performance of the models at high sampling frequency is significantly higher than that of low sampling frequency.
- The performance of model 2 is significantly higher than that of model 1 and model 3. The performance of model 1 and the performance of 3 are almost similar with model 3 being slightly inferior.
- The standard deviation amongst the performance of the model for 5-folds is smaller for higher SNR levels and higher sampling frequency dataset.

It can be concluded that model 2, that is, complex-valued CNN model with spectrograms as inputs performs significantly better as compared model 1 and model 3. This indicates that both magnitude and phase of the complex valued inputs contribute in improving the performance of the drone detection. It can also be concluded from the observations that the proposed models can detect a drone in small signal duration if the

TABLE III

PERFORMANCE METRICS (IN%)

Model	Model 1			Model 2			Model 3		
SNR	5dB	10dB	15dB	5dB	10dB	15dB	5dB	10dB	15dB
Set A	Accuracy= 56.65 ± 0.56 Precision=54.21 ± 0.71 Recall= 86.58 ± 8.84 F1-score= 66.46 ± 2.51	Accuracy=70.53 ± 1.18 Precision=65.59 ± 2.07 Recall=87.13 ± 6.07 F1-score= 74.66 ± 1.40	Accuracy=83.51 ± 1.32 Precision= 78.13 ± 3.33 Recall=93.39 ± 3.69 F1-score=84.95 ± 1.40	Accuracy=66.62 ± 0.16 Precision=64.76 ± 0.95 Recall=72.94 ± 3.26 F1-score=68.56 ± 1.3	Accuracy=81.28± 0.86 Precision=75.79 ± 0.93 Recall=91.94 ± 3.19 F1-score=83.05 ± 1.20	Accuracy=87.92 ± 0.76 Precision=83.19 ± 1.45 Recall=95.17 ± 3.76 F1-score=88.70 ± 1.05	Accuracy=54.03 ± 2.27 Precision= 53.42 ± 1.17 Recall= 63.04 ± 7.33 F1-score=57.65 ± 3.35	Accuracy=74.44 ± 1.07 Precision=71.10 ± 1.01 Recall=82.41 ± 4.32 F1-score=76.27 ± 1.71	Accuracy= 83.78 ± 0.65 Precision=80.82 ± 1.90 Recall=88.70± 3.25 F1-score=84.51 ± 0.95
SetB	Accuracy=61.93± 0.99 Precision=59.43 ± 1.24 Recall=76.14 ± 10.48 F1-score=66.36 ± 3.62	Accuracy=72.07 ± 0.96 Precision=67.93 ± 1.52 Recall=83.91 ± 4.33 F1-score=74.99 ± 1.33	Accuracy=83.71 ± 1.22 Precision=79.15 ± 1.45 Recall=91.54 ± 2.55 F1-score= 84.87 ± 1.38	Accuracy=70.15 ± 2.91 Precision=67.97 ± 1.33 Recall=76.07 ± 11.03 F1-score=71.40 ± 5.35	Accuracy=82.21 ± 1.72 Precision=77.86 ± 1.33 Recall=90.17 ± 5.07 F1-score= 83.47 ± 1.90	Accuracy=91.20 ± 1.12 Precision=86.46 ± 2.23 Recall=97.80 ± 0.86 F1-score=91.76 ± 0.97	Accuracy=59.63 ± 0.90 Precision=57.64 ± 1.46 Recall=73.33 ± 4.58 F1-score=64.44 ± 1.28	Accuracy=74.64 ± 2.13 Precision=69.91 ± 1.56 Recall=86.30 ± 3.98 F1-score=77.23 ± 2.44	Accuracy=85.93± 0.56 Precision=82.26 ± 2.50 Recall=91.91 ± 4.39 F1-score=86.69 ± 0.93
SetC	Accuracy=76.20 ± 0.96 Precision=70.00 ± 0.96 Recall=91.84 ± 3.74 F1-score=79.39 ± 1.00	Accuracy=84.86 ± 0.82 Precision=79.43 ± 1.57 Recall=94.07 ± 2.72 F1-score=86.09 ± 1.20	Accuracy=91.76 ± 0.88 Precision=88.29 ± 1.08 Recall=96.27 ± 1.51 F1-score=92.10 ± 0.93	Accuracy=79.47 ± 0.41 Precision=73.87 ± 0.86 Recall=91.22 ± 1.39 F1-score=81.62 ± 0.30	Accuracy=88.36 ± 0.57 Precision=83.04 ± 0.89 Recall=96.44 ± 1.12 F1-score=89.23 ± 0.51	Accuracy=93.80 ± 0.44 Precision=90.06 ± 0.48 Recall=98.46 ± 1.22 F1-score=94.06 ± 0.49	Accuracy= 75.37 ± 0.53 Precision=70.55 ± 1.48 Recall=87.41 ± 4.80 F1-score=77.96 ± 1.19	Accuracy=84.23 ± 0.55 Precision=79.85 ± 0.57 Recall=91.55 ± 1.03 F1-score=85.31 ± 0.61	Accuracy=91.09 ± 0.45 Precision=87.83 ± 1.31 Recall=95.45 ± 1.88 F1-score=91.46 ± 0.55

sampling frequency is high. The highest accuracy, precision, recall and F1-score with lowest standard deviation for drone detection is achieved by model-2 for input set C at SNR 15dB. An evaluation of execution times for the proposed models for input set C at SNR 15dB is given in Table IV. It can be observed that Model 2 has a longer execution time as compared to model 1 but it performs significantly better than model 1 as well.

TABLE IV

EXECUTION TIME OF THE PROPOSED MODELS

Model	Model 1	Model 2	Model 3
Time (in s)	4675	6658	7865

V. CONCLUSION

A classification algorithm based on complex-valued CNN was used to detect drones from radar time series. Performance analyses of three CNNs:

- a real-valued CNN taking the magnitude of the spectrograms as inputs,
- a complex-valued CNN taking complex-valued spectrograms as inputs,
- a complex-valued CNN taking the raw complex radar time series as inputs.

were carried out using simulated datasets. For each simulated dataset, the **complex-valued CNN** with **complex-valued spectrograms** as inputs outperforms the two other models. The execution time of complex-valued CNN is found to be higher than real-valued CNN. Albeit this, the complex-valued CNN provides better drone detection and therefore is a good candidate for drone detection based on radar time series.

ACKNOWLEDGMENT

This work was financially supported by Natural Sciences and Engineering Research Council of Canada (NSERC), General Dynamics Mission Systems, and Defence Research and Development through a collaborative research and development (CRD) grant.

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