Classification of Small Radar Cross Section Targets with Convolutional Neural Networks (CNNs)

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Abstract– Abstract-In the recent years, drones were used widely in many useful applications as civil, medical, agriculture and military and made a big success in these applications. This made evil people to use drones in some malicious applications which are forbidden by the law. So, nowadays, classification of drones is one of the most important objectives for the researchers to decrease crimes made by these drones. Classification of drones, nowadays, is made using radars due to it is working without respect to the weather, so the radars must be trained for this work. The best way to train the radars is Artificial Intelligence specially with CNNs Deep Learning method which select the target features itself without needing to human interference. Also, as known that the RCS of drones is comparable with birds and this leads researchers to create much more accurate algorithms to have the best classification accuracy. In this paper we used 17000 samples for classification, 16000 for radar training and 1000 for testing.

I. Introduction (Heading 1)

Recently, unmanned aerial vehicles (UAVs) have captured the interest of the academy, industry and general public due to their enormous potential. the commercial use of unmanned aerial vehicles (UAVs), also known as drones, have exploded. Current studies estimate that the global market will hit $127 billion in 2020 [1]. According to the Federal Aviation Administration of the US, there were registered over 670.000 drones only in the US in 2017, and it is prospected that over seven million drones will be sold in 2020 [2]. Mini drones have played a vital role in the development of smart cities. they are useful in a wide range of applications such as: cinematography, agriculture, mapping, forensics, stockpile measurements, shipping, law enforcement, mobile communication and many others. drones can be used as a safe and cost-effective solution for many kinds of problems. And this also opens the door for malicious use. There have already been cases of privacy violations, smuggling of illegal substances, collision hazards, and deployment of explosive weapons [3]. Therefore, police and security agencies must have the right equipment to deal with this new aerial thread. Undoubtedly, it is more difficult to detect drones due to their small dimensions relative to other moving objects, so radar systems have been proved to be a good solution for early detection of these kinds of threats. a deep learning-based automatic recognition system has been developed, which will provide high-level interpretations (target type and location) to the operator, a convolutional NN (CNN) has been implemented, which takes as input arrays of range–Doppler radar data, and predicts their class (a car, a person, or a drone). It is known that the proper performance of the CNN depends on the availability of high-quality training data [4]. With the integration of radar systems and these CNNs algorithms with a dataset, the classification of drones may be easy and fast. In this paper we discuss the CNNs method with radar systems to solve the problem of classification of the drones with high accuracy and to decrease the forbidden jobs made by drones. And we used 17000 samples, 16000 for training and 1000 for testing.

II. Signal processing

For detection and classification purposes, the Linear Frequency Modulated (LFM) signal is the best to have better, more accurate results and to have Doppler frequency for the target. The received signal is the input for matched filter of the radar system. The output of the matched filter sent to CFAR. The output of CFAR is then analyzed by Empirical Mode Decomposition (EMD). Then the output is processed by Short Time Fourier Transform (STFT). Finally, CNN classifiers are used to classify the targets [2] [3].

A. *Linear Frequency Modulated (LFM) Signal*

CW radars to be able to measure target range, the transmit and receive waveforms must have some sort of timing marks [13]. By comparing the timing marks at transmit and receive, CW radars can extract target range. The timing mark can be implemented by modulating the transmit waveform, and one commonly used technique is Linear Frequency Modulation (LFM) as shown in figure 1 [13]. LFM waveform x(t) is given by

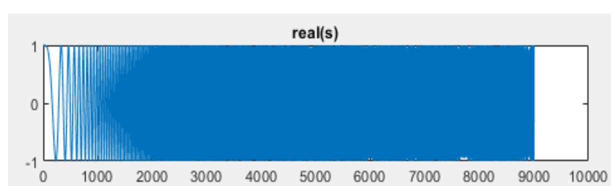

Fig. 1 Generating LFM signal.

Continuous Wave radars may use LFM waveforms so that both range and Doppler information can be measured. In practical CW radars, the LFM waveform cannot be continually changed in one direction, and thus, periodicity in the modulation is normally utilized. The modulation does not need to be triangular; it may be sinusoidal, saw-toothed, or some other form. LFM can detect both range and Doppler frequency of the target so it is better than phase coded signals [13] [11].

B. *Matched Filter*

The unique characteristic of the matched filter is that it produces the maximum achievable instantaneous SNR at its output when a signal plus noise are presented in the input [13]. There are some steps to obtain the matched filter of the signal as

1- Applying Fast Fourier Transform (FFT) for the input signal
2- Making the reference signal from the transmitted signal by applying the conj. FFT

We make convolution for these two signals then applying the Inverse FFT (IFFT) to have our desired SNR from the matched filter, as shown in figure 2.

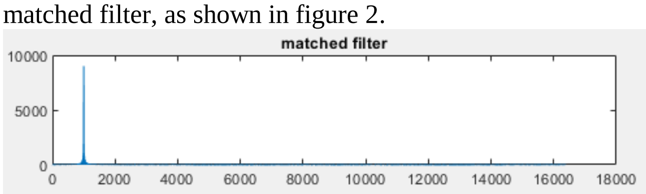

Fig. 2 The LFM auto-correlation function.

C. *Signal Denoising Using Empirical Mode Decomposition*

EMD is an algorithm which decomposes non-stationary time series into sum of Intrinsic Mode Functions (IMFs) which represent zero mean amplitude and frequency modulated components and an almost linear component called residual, as shown in figure 3. EMD doesn't need any priory defined basis system and doesn't constrained by conditions to work. EMD is used to decompose the composite signal into its single frequencies [13]. Its formula is expressed as follows:

$$x(t) = \sum x(t) + r(t) \qquad (1)$$

E. Short Time Fourier Transform

Short Time Fourier Transform (STFT) is used to convert dataset signals into spectrogram. The spectrogram, by definition, displays the energy/intensity distribution of the signal along the time-frequency axis.as shown in figure 4. CNN is used to classify drones and it has been implemented, which takes as input arrays of range Doppler radar data, and predicts their class which is the output of STFT. It is known that the proper performance of the CNN depends on the availability of high-quality training data [2] [4].

III. Classification with Deep Learning

Artificial Neural Networks (NNs) have grown in popularity in the recent years and achieved good results in the application of classification of drones, especially Convolutional Neural Networks (CNNs) [5]. edicts their class (a car, a person, or a drone). It is known that the proper performance of the CNN depends on the availability of high-quality training data, which should be collected and labelled in real and representative scenarios.

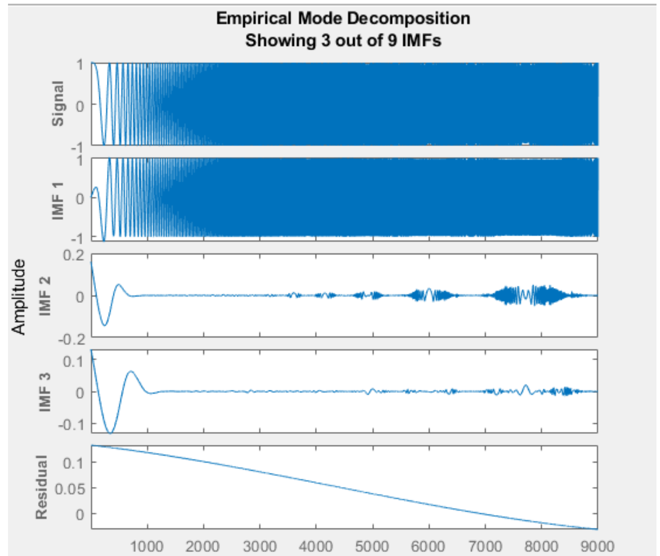

Fig. 3 EMD components.

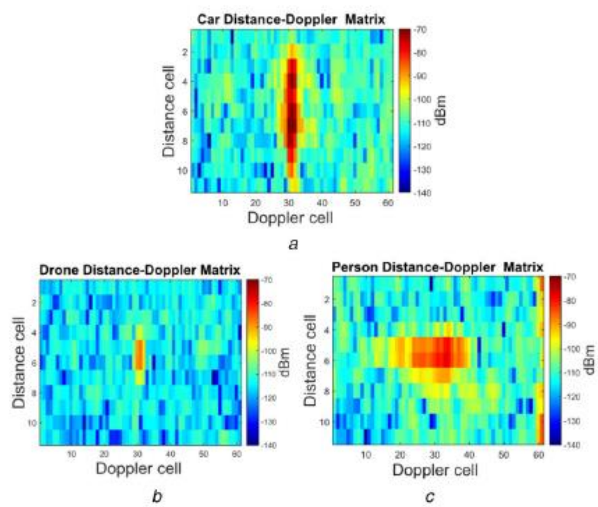

Fig. 4 2D Range-Doppler representation for a) car, b) drone, c) person

UAV classification and recognition based on radar information can be split into two groups: based on handcrafted features (where features are manually selected through oriented signal processing techniques) and based on deep-learning features (the own classification algorithm computes the best possible features for the target task) [8].

A. *Handcrafted Feature Techniques*

The proposed signal representation, called two-dimensional (2D) complex regularized spectral analysis, is based on the magnitude and phase information of the Fourier transform, producing a complex log spectrum. Also, classical spectrogram, spectrogram, and cadence velocity diagram (CVD) are added to the feature vector to increase its discriminability [10]. To remove the unreliable feature dimensions, a subspace reliability analysis (SRA) is proposed and compared with standard principal component analysis (PCA). There has been also some effort in using wavelet transform (WT) as a feature for classification. In contrast with the Fourier transform, the WT preserves the time information.

This allows to simultaneously analyses frequency and time variations in a multiresolution space, as opposed to STFT, where the resolution is determined by the depth of the FT. an improved Doppler resolution does indeed provide more useful information, which benefits the potential classification opportunities involving small drones [9].

B. Deep-learning feature techniques

In contrast to handcrafted features approaches (where most of the effort is the selection of adequate features to represent the different classes), there has been some research focused on learning from data the optimal features for the target application [7]. Some researchers used the pre-trained ‘GoogleNet’ CNN to process the spectrograms and CVDs collected from two flying drones. Other researchers used a deep belief network (DBN) to classify three different types of micro-drones. Finally, researchers achieved a good resolution and accuracy by using these deep learning algorithms [11].

C. CNN Classifiers:

It started in 1999 by LeNet-5 and after updates we now has some advanced models by Google. Nowadays, the world goes to have the lightweight design and increasing the hidden layers to have better accuracy [6]. The developed CNN is oriented to run in embedded systems to provide real-time target recognition for the radar operators. This restricts the total number of network parameters (and, therefore, layers) to consume few computational, power, and memory resources [5]. CNNs have excellent performance and have been applied widely to image classification and recognition [6]. CNNs is the best DL method to be used in radar applications specially in classification of drones due to:

1- It is able to deal with any size of dataset.
2- It has higher accuracy than the SVM method due to the hidden layers.
3- It can extract much more features than SVM and Auto encoders methods.

CNNs rely entirely on a large amount of labeled training data for supervised optimization, the use of a large training database increases the likelihood of convergence to a good solution, and the alterations of the image (e.g., flipping, rotating, scaling) used to generate new samples and added to the training data set to have higher accuracy [12]. It is constructed from three principles layers:

1- convolutional layer: localized convolutional filtering to capture the local features of input images.
2- pooling layer: a max pooling layer follows each convolutional layer, in which local maxima are used to reduce computational complexity in the forward layers.
3- fully connected layer: fully connected layers are used to learn nonlinear combinations of extracted features from previous layers, as shown in figure 5.

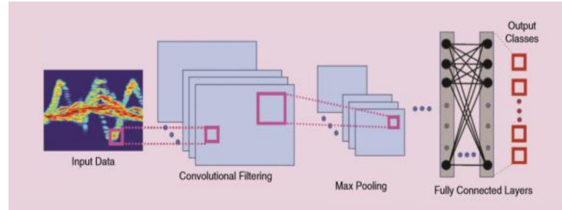

Fig. 5 Structure of CNN layers

IV. Results

This section starts showing the effect of using multiple consecutive frames in the recognition performance, and finishes comparing the proposed CNN with other state-of-the-art networks on the created radar database. Next, two state-of-the-art embedded networks are compared with the proposed CNN: MobileNetV2 and NasNet. These are specifically designed for running in embedded systems and have demonstrated good performance. MobileNetV2 is based on depth wise separable convolutions that allow very memory-efficient inference. It has obtained very good performance on the ImageNet dataset. NasNet has been also used for image classification and proposes a new regularization technique, called Scheduled Drop Path, to outperform the generalization capability. All the previous networks have been tested on our dataset. Figures 6-8 shows the confusion matrices of MobileNetV2, NasNetMobile and DopplerNet. They get a mean accuracy of 0.9894 for MobileNetV2, 0.9769 for NasNetMobile and 0.9948 for the proposed network, DopplerNet.

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