DEEP LEARNING-BASED COGNITIVE RADAR SYSTEM FOR MICRO-UAS DETECTION AND CLASSIFICATION

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ABSTRACT

This paper proposes a low-cost cognitive radar system that exploits deep learning and 2.4 GHz continues wave Doppler radar sensing techniques for detecting and identifying micro unmanned aerial systems (micro UASs). The proposed architecture, employes the spectral correlation function (SCF), which is a Doppler radar-based method that has high resilience to environmental noise, to generate the unique pattern signatures for the individual micro UASs. Furthermore, a low-complexity binarized convolutional neural network (CNN) is designed to detect and identify the micro UASs by recognizing the SCF-based pattern signatures. By employing the low-complexity CNN, the computationally costly 617632 floating point multiplication operations required in the conventional CNN are represented by zero computational cost no connections, simple connections, negation operations, bit-shifting operations, and bit-shifting with negation operations. The simulations evaluate the performance of the proposed Low-complexity CNN in detecting and identifying the micro UASs by comparing the accuracy achieved by the proposed method with that is obtained by using the conventional CNN.

1. INTRODUCTION

Micro unmanned aerial systems (micro-UASs) are remotely controlled or autonomous small scaled aerial systems. They are low-cost devices with small dimensions and weights and also referred as "drones". In recent years, micro-UASs are becoming increasingly popular among hobbyist and also for a variety of applications such as performance art, aerial photography and video, search and rescue mission, precision agriculture, mapping and surveying, and package delivering [1]. Despite these useful applications, misuses of micro-UASs are also becoming a concerning threat to the public. Micro UASs have been reported to interfere with aircraft [2, 3]. A micro-UAS was crashed at the White House, raising concerns about security risks [4]. The micro-UASs can also be used as spying devices which violate the privacy of civilians and the government and private organization.

Radar sensing is one of the most effective methods adopted by defense mechanisms for detecting aerial systems. However, because of the small size and slow moving speed, the micro UASs are undetectable by the conventional radar systems designed to detect larger and fast-moving aerial systems. As one type of non-radar techniques, acoustic signal processing has been widely used in detecting micro-UASs [5]. Acoustic signal processing-based techniques are effective but not resilient to environmental noise. Another existing non-radar technique is to detect the radio frequency signals that are used for the remote control of the micro-UAS [6]. This method may not be appropriate for fully autonomous micro-UASs. Some of the other existing non-radar strategies include video-based detection and thermal based detection [6]. Recently some radar-based systems have also been proposed for detecting and identifying micro-UASs. In [7], Drozdowicz *et al.* discussed an experiment conducted for the detection and tracking of micro-UASs using a radar system. In [8], Shin *et al.*, proposed a K-band radar system with fiber-optic links for detecting micro-UASs. In [9], Jahangir *et al.* used 2-D L-Band receiver arrays to detect micro-UASs. In this method, decision tree machine learning technique was utilized to reject other targets. In our previous work, we proposed a low-cost 2.4 GHz continuous-wave Doppler radar sensor built using commercially available RF components along with a signal processing mechanism that uses spectral correlation function (SCF) to generate noise-resilient and distinguishable 2-D signature patterns and deep belief network (DBN) based classifier for detection and identification of micro-UASs [10, 11].

Deep learning methods are artificial neural network (ANN) based machine learning techniques having multiple layer hierarchies of ANNs. These techniques are more effective in extracting hierarchical features from raw data [12]. Deep learning methods have been used for pattern recognition in various application areas [13–17]. Convolutional neural networks (CNNs) are one of the most successful deep learning techniques inspired by the neuron arrangement of the visual cortex of mammals [18]. CNN-based methods are widely used for image classification tasks including radar signature analysis [19–22].

The main challenge of implementing deep learning methods is the high computation-complexity that increases the power and area cost of digital implementations for deep learning based classifiers. High computation-complexity is a result of the high number of floating-point multiplications operations. In our previous work, we proposed a multiplierless low-complexity DBN with direct mapping to binary logic circuits. In this work, we use a multiplierless CNN-based classifier for detecting and identifying micro-UASs SCF patterns. In [23], Lin *et al.* proposed a binarization method for backpropagation algorithm which produces binary weights $\{-1, 0, 1\}$. In this paper, we adopt this method to realize the multiplierless low-complexity CNN.

In the following section, we provide an overview of the proposed system. Sections 3, 4, and 5 briefly discuss the proposed radar sensor, SCF pattern generation, and the low-complexity CNN, respectively. The conducted experiment and the results obtained are summarized in Section 6. In Section 7, the conclusions and future work are presented.

2. OVERVIEW

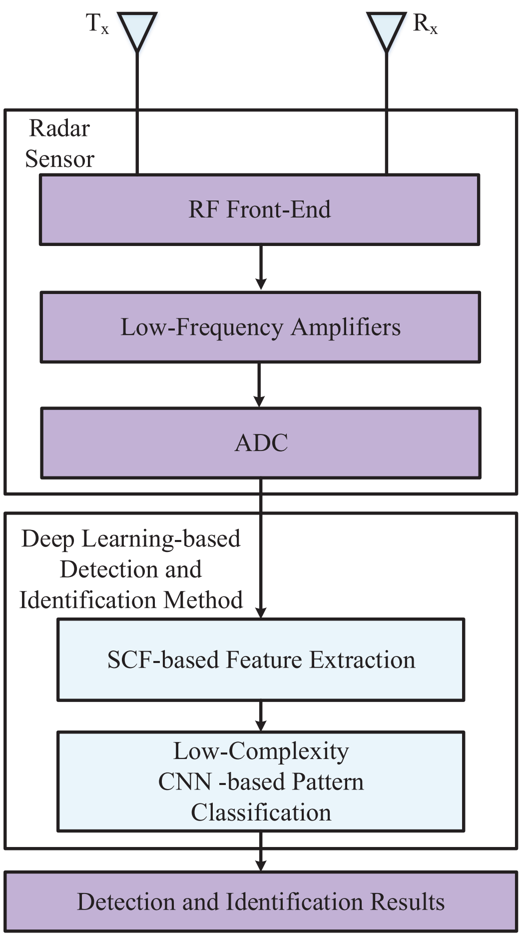

Figure 1: Overview of the proposed system.

As shown in Fig. 1, the proposed system consists of the radar sensor and the deep learning-based detection and identification method. The radar sensor is formed with a Doppler radar RF front-end, low-frequency amplifiers, and an analog to digital converter (ADC) system. Relevant low-frequency Doppler shifts are amplified with low-frequency amplifiers and ADC is used to sample the signals for further digital signal processing. Deep learning-based detection and identification method contains a spectral correlation function (SCF)-based feature extraction method followed by the low-complexity CNN-based pattern classifier, which classifies the generated SCF patterns to detect and identify micro UASs presence within the radar beam.

3. RADAR SENSOR

Figure 2(a) illustrates the block diagram of the radar sensor presenting the details of the radar front-end. The front-end of the radar sensor is a Doppler radar system for capturing frequency shifts induced on reflected electromagnetic waves. 2.4GHz continues-wave interrogation waveform is transmitted through the transmitter Tx and the reflected waves are captured by the receiver Rx. The moving propellers of micro-UASs cause mechanically induced phase modulations on the reflected signal that produces Doppler shifts.

A bandpass filter is used to filter out the noise in the received signal through Rx. Low noise amplifiers (LNAs) are used to boost the filtered received signal. The amplified signal is mixed with in-phase (I) and quadrature (Q) components of the transmitted signal. A phase-shifter (90-degree hybrid) is used to generate the I and Q components of the transmitted signal. The I/Q based method is employed to eliminate the possible effects of null points. In order to extract the induced Doppler shifts, lowpass filters are applied on the mixer output signals. Low-frequency amplifier stage with lowpass filtering of 100 Hz cut-off frequency is used to extract and boost the useful Doppler frequency shifts for micro-UAS detection and classification. ADC is used to sample and record the boosted signals for further processing. The practical implementation of the radar sensor is shown in Fig. 2(b). Doppler radar front-end is implemented using commercially available RF components, low-frequency amplifiers are implemented with low-cost analog components. National Instruments data acquisition unit is used as the ADCs.

4. SCF SIGNATURE PATTERNS

Cyclic Autocorrelation Function (CAF) is defined to quantize the amount of correlation between different frequency shifted versions of a given signal and represent the fundamental parameters of their second order periodicity [24]. CAF is calculated as follows:

$$R_x^{\alpha}[l] = \left[\lim_{N\to\infty} \frac{1}{2N+1} \sum_{n=-N}^{N} x[n]x^*[n-l]e^{-j2\pi\alpha n} \right] e^{-j\pi\alpha l} \tag{1}$$

Where $x[\cdot]$ is the given signal and $\alpha = m/T_0$ is the cyclic frequency, when T_0 is the process period, and m is an integer. Spectral correlation function (SCF) is the Fourier transform of CAF, f the temporal frequency of the given signal SCF is calculated as follows:

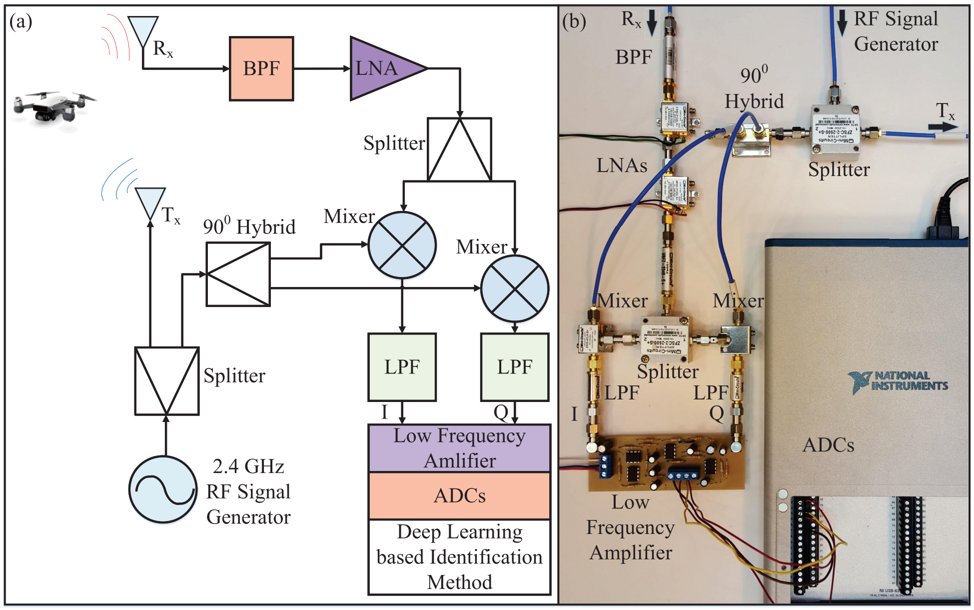

Figure 2: (a) System architecture of our proposed deep learning-based AMC method; (b) Implementation of radar sensor.

$$S_x^{\alpha}[f] = \sum_{l=-\infty}^{\infty} R_x^{\alpha}[l] e^{-j2\pi f l} \quad (2)$$

For signals that have different modulation schemes, it has been shown that the SCF provides unique peak profiles because of their modulation types [24]. Because that the propeller motions of micro UASs induce the Doppler effect mechanically, which can be considered as the phase modulation characterizing the unique physical properties of different types of micro UASs, it is possible to observe a distinguishable peak profile on SCF of the extracted Doppler radar signal for each type of micro UASs [25].Another advantage of using the SCF patterns is since the SCF suppresses stationary features, our method is resilient to stationary impairments such as additive white Gaussian noise (AWGN) [24].

5. LOW-COMPLEXITY CNN

As shown in the Fig. 3, the CNN designed in our work consists of 3 convolution layers, 2 pooling layers, a fully connected layer with rectifier linear units (ReLU), and a softmax-based output layer. The inputs to the CNN are 2D images having the size of 24×24. The first convolution layer evaluates 32 features with 5×5 kernel size. Maximum pooling is performed after the first convolution layer with the kernel size of 2×2, which reduces the image size to 12×12. The second convolution layer evaluates 32 features with 5×5 kernel size along with 2 maximum pooling, which reduces the size of the image to 6×6. The third convolution layer evaluates 32 features with 2×2 kernel size. The outputs of the 32 kernels of the third convolution layer are reshaped and combined to form a vector of the size $6 \times 6 \times 32 = 1152$.

Table 1: The floating-point multiplication operations required in CNN.

Layer	Floating point Multiplications
Convolution layer 1	$24 \times 24 \times 5 \times 5 \times 32 = 460800$
Convolution layer 2	$12 \times 12 \times 5 \times 5 \times 32 = 115200$
Convolution layer 3	$6 \times 6 \times 2 \times 2 \times 32 = 4608$
Fully connected ReLU	$1152 \times 32 = 36864$
Fully connected softmax	$32 \times 5 = 160$
The Number of Required Multiplications	617632

A fully connected layer with 1024 ReLU units is added on top along with a softmax layer for classification.

If the weights of the convolution layers and fully connected layers remain as floating-point numbers, the total number of floating point multiplication operations required to perform in a single iteration of testing is shown in Table 1. We assume the number of class labels as 5. Since floating point multiplication is computationally expensive in digital logic and the number of the total multiplications required for the CNN is very high, the deployments of the above CNN becomes a hardware-expensive task. By modifying the backpropagation algorithm of the CNN as shown in Table 2, we replace the floating-point weights of the CNN by using five possible values $-2^p, -1, 0, 1, 2^p$, where p is a positive integer. By doing so, we reduce the hardware-expensive floating-point multiplications to the operations that are much less costly in the digital hardware as shown in Table 3.

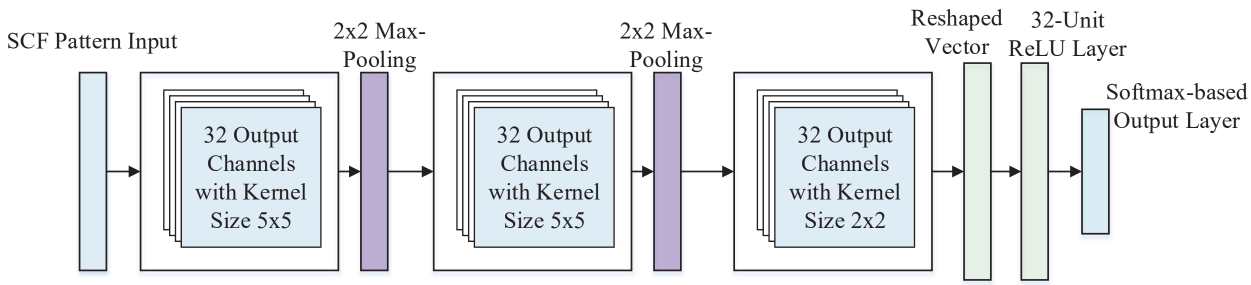

Figure 3: The structure of CNN.

Table 2: The training algorithm for updating our low-complexity CNN.

Operators and functions:
. $\geq$: the elementwise more than or equal comparison of two matrices.
.$\times$: the elementwise multiplication of two matrices.
$y = sign(x)$: if $x < 0$, $y = -1$, else $y = 1$.
$y = absolute(x)$: if $x < 0$, $y = -x$, else $y = x$.
$\mathbf{Y} = rand(\mathbf{X})$: randomly assigns $y_{ij} \in [0, 1]$ and $dim(\mathbf{Y}) = dim(\mathbf{X})$.
$y = cast(x)$: if $x = true$, $y = 1$, else $y = 0$.
$\mathbf{W} = backprop(\mathbf{W}, f)$: applies the gradient descent based backpropagation algorithm to fine-tune the weight matrix $\mathbf{W}$, where f is a batch of training data.
$f = nextbatch(\mathbf{F}, batchsize)$: returns the next batch of training data according to batch size, where $\mathbf{F}$ is the training data set.
$\mathbf{W_c} = clipping(\mathbf{W}, L)$: clips the element values of weight matrix $\mathbf{W}$ to be in the range $[-L, L]$ where L is a predetermined scalar.

Inputs: L-clipping level, $\mathbf{W}$-initial weight matrix , $\mathbf{F}$-training data, $\mathbf{T}$-labels corresponding to training data, N-number of training iterations.

Output: $\mathbf{W_b}$-binarized weight matrix ($w_{ij} \in \{-1, 0, 1\}$)

Steps:
For $epoch \leqslant N$
  $f = nextbatch(\mathbf{F}, 50)$
  $\mathbf{W} = backprop(\mathbf{W}, f)$
  If $(mode(epoch, 100) = 0)$
    $\mathbf{W_c} = clipping(\mathbf{W}, L)$
    $\mathbf{S} = sign(\mathbf{W_c})$
    $\mathbf{P} = absolute(\mathbf{W_c})/L$
    $\mathbf{T} = \mathbf{P}. \geq rand(\mathbf{P})$
    $\mathbf{W_b} = cast(\mathbf{T}). \times \mathbf{S}$
  End
End

Table 3: Digital logic mapping of multiplications with low-complexity weights.

Weight Value	Mapping
0	No connection
1	Connection
-1	Negation
2^p	Right shift by p bits
-2^p	Right shift by p bits and negation

6. EXPERIMENT AND RESULTS

The proposed radar sensor is set up in the laboratory environment and the experiment is conducted using four types of micro-UASs. First, the Doppler radar sensor is operated with the micro-UASs whose positions are fixed in front of the radar beam. The time series data collected from the ADC are used to generate a set of reference SCF patterns that is used as the pattern signature for the scenario in which no micro-UASs presented. Then micro-UASs are clamped in front of the radar beam by a distance of 3 meters from the transmitter and receiver antennas to a reasonable far-field approximation at the radar frequency of 2.4 GHz. The time series are collected while the propellers of each micro-UAS are in motion. The collected time series are used to generate a set of SCF pattern signatures for each type of micro-UAS. Figure 4 shows the micro-UASs used in the experiment and Fig. 5 shows the example SCF patterns for reference and for each micro-UAS. Furthermore, in our experiment, SCF patterns are generated using a MATLAB Communications System Toolbox functions on experimentally collected data [26].

Pre-processing and training

The gray-scale images of the SCF patterns are resized to be 48×48 images. Fast Fourier transform (FFT) based method is used for image scaling. A 2-dimensional (2D) FFT operation is implemented on the original grayscale images and a 48×48 pixel square is selected from the center of the FFT transformed image. Then inverse 2D FFT is performed to achieve the scaled down image. By doing so, high-frequency components of the original image are filtered out, and thus high-frequency noise

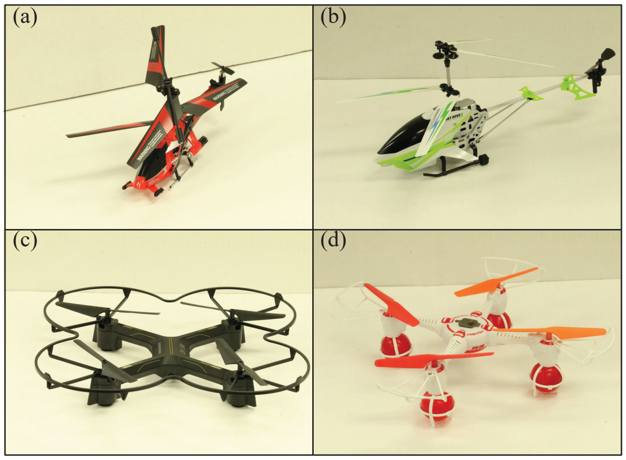

Figure 4: Micro-UASs used in the experiment; (a) Type 1; (b) Type 2; (c) Type 3; (d) Type 4.

is removed from the scaled down image. Considering the symmetry of the patterns, a quarter of the pixels from the resized images is used as the input for the low-complexity CNN classifier. Therefore, the input size of the low-complexity CNN is 24×24.

The low-complexity CNN is trained using 1000 SCF pattern data that includes 200 patterns corresponding to each micro-UAS and the reference. As a comparison, a conventional CNN, which has the same structure but uses floating-point accurate weights, are also trained with the same 1000 training data. Another 50 patterns from each category are used to evaluate the performance of the CNN. The classifiers based on low-complexity and conventional CNNs are implemented using TensorFlow APIs [27]. In the simulation, we set the number of iterations as 1000 and the batch size to be 20. At each 100th iteration of backpropagation training, binarization is performed for the low-complexity CNN. The simulation results are illustrated in the following subsection.

Results

Tables 4 and 5 present the confusion matrices for the TensorFlow implementations of conventional and low-complexity CNNs, respectively. In Tables 4 and 5, the rows represent the actual class that each testing SCF pattern belongs to and the columns are the classes identified by using the conventional and low-complexity CNNs.

The overall detection accuracy of micro-UASs by using conventional CNN based classifier is 98%, and that achieved by using the low-complexity CNN based classifier is 96.5%. The rates of false alarm for the conventional and low-complexity CNNs are 0.5% and 2%, respectively. Figure 7 compares the performance of the these two considered CNNs in classifying micro-UASs.

Based on the simulation results shown in Figs. 6 and 7, we can observe that the low-complexity CNN achieves comparable accuracy in detection and identification of micro UASs compared with that achieved by conventional CNN. Furthermore, our proposed CNN outperforms the conventional CNN in low computational complexity. Overall, our proposed CNN achieves a good tradeoff between the performance and the computational complexity.

Table 4: Classification of SCF patterns for micro-UAS detection and identification using TensorFlow implementation of conventional CNN.

Actual	Classification from CNN				
Pattern	Type 1	Type 2	Type 3	Type 4	Ref.
Type 1	48	0	2	0	0
Type 2	0	48	0	1	1
Type 3	0	0	50	0	0
Type 4	0	0	0	50	0
Ref.	1	0	0	0	49

Table 5: Classification of SCF patterns for micro-UAS detection and identification using TensorFlow implementation of low-complexity CNN.

Actual	Classification from Low-Complexity CNN				
Pattern	Type 1	Type 2	Type 3	Type 4	Ref.
Type 1	46	0	2	0	2
Type 2	0	48	1	0	1
Type 3	0	0	50	0	0
Type 4	0	0	0	49	1
Ref.	1	1	0	0	48

7. CONCLUSION

In this paper, we propose a deep learning-based cognitive radar system for detecting and identifying micro-UASs by using SCF function and low-complexity CNN method. The proposed system consists of a low-cost radar sensor and a digital signal processing subsystem that exploits the noise resilient SCF to generate unique signature patterns of the individual micro-UASs and uses the low-complexity CNN to classify the patterns. Our proposed low-complexity CNN has the advantage of containing no multipliers while a conventional CNN with the same structure requires performing 617632 floating-point multiplication operations. As illustrated in the simulation results, although the low-complexity CNN shows lower accuracy compared with the conventional CNN the accuracy of detection and identification is are acceptable especially considering the low computational cost.

During the experiments for the work in this paper, we kept the micro UASs immobile and leverage the Doppler shifts induced by propeller movements. In our future work, we plan to conduct the experiments by using moving micro UASs and we also plan to set up the radar system for real-time detection of micro-UASs.

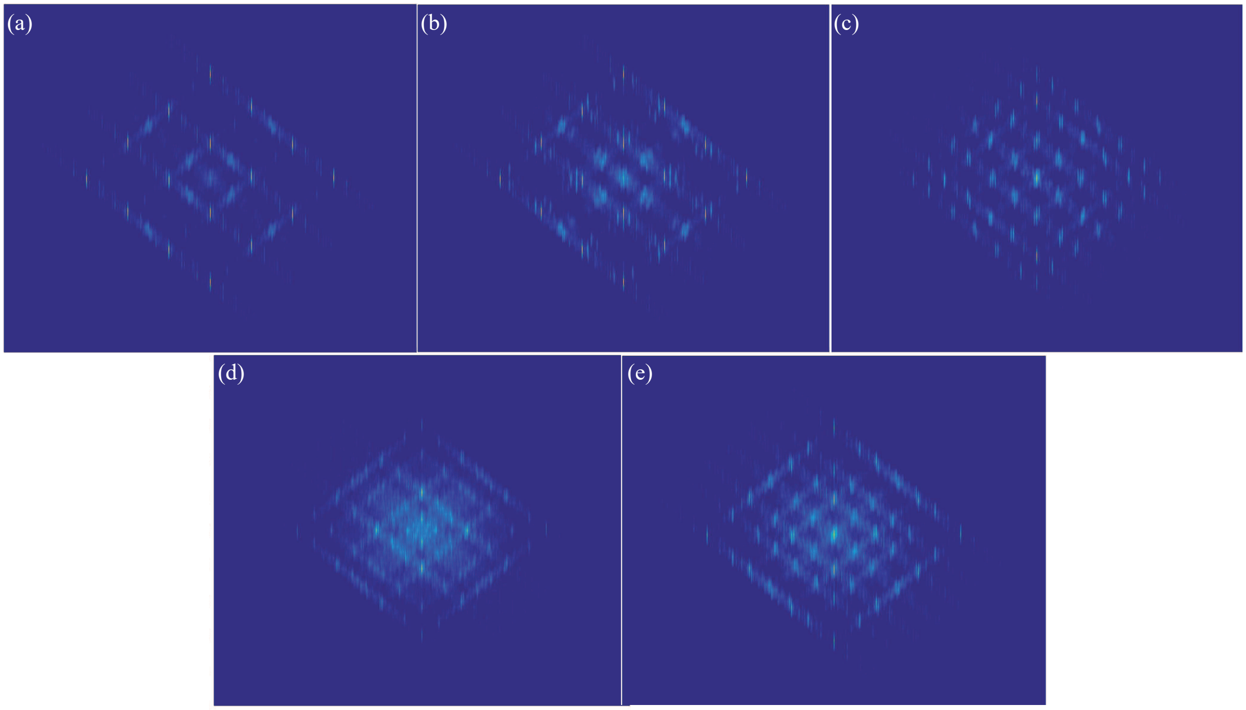

Figure 5: Example SCF patterns for (a) Reference (When there is no micro-UAS); (b) Type 1; (c) Type 2; (d) Type 3; (e) Type 4.

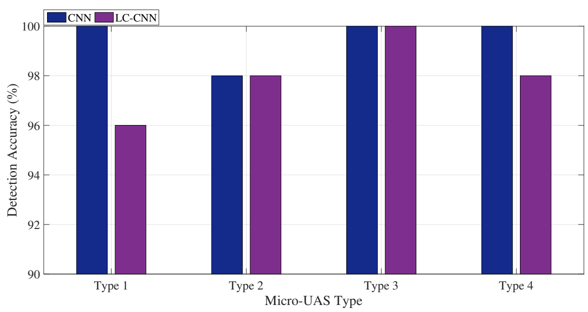

Figure 6: Comparison between the accuracies in detecting each type of micro-UAS achieved by using the conventional CNN and low-complexity CNN.

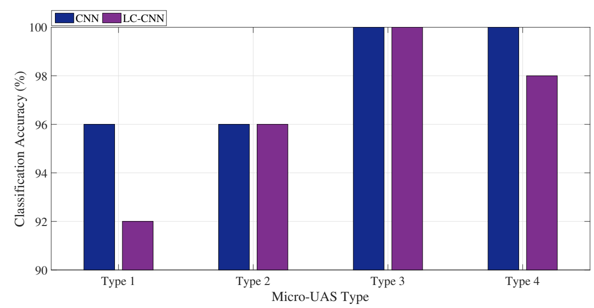

Figure 7: Comparison between the accuracies in identifying each type of micro-UAS achieved by using the conventional CNN and low-complexity CNN.

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