Micro-motion Classification of Rotor UAV and Flying Bird via CNN and FMCW Radar

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Abstract. Aiming at the problem that it is difficult to recognize flying birds and rotary-wing UAVs by radar, a micro-motion feature classification method based on multi-scale convolutional neural network (CNN) is proposed in this paper. Using the K-band frequency modulated continuous wave (FMCW) radar, data acquisition is performed on the rotor UAV and flying bird targets in indoor and outdoor scenes, and then the feature extraction and parameterization of the micro-Doppler signal are performed using time-frequency analysis technology to construct the radar feature dataset. A novel type of multi-scale CNN is designed, which can extract the global and local information of the target's micro-Doppler features and improve the classification accuracy. Validation of measured data shows that the classification probability of rotary-wing drones and flying bird targets can reach higher than 98% by using the proposed algorithm, which provides a new technical and practical approach for the identification of low and slow small targets.

Keywords: Radar target classification · Micro-motion · Flying bird · Rotor UAV · FMCW radar · CNN

1 Introduction

Bird strikes refer to incidents of aircraft taking off or landing or colliding with birds during flight. It is a traditional security threat in the takeoff and landing phase of flights. Recently, "low, slow and small" aircraft represented by small UAVs, i.e., drones, have been developing rapidly [1]. There have been successive incidents of "black flying" of drones in many airports. Illegal flying of drones has become a new problem together with the "bird strike", which may threaten the safety of flights around the airport's clear area. At present, the surveillance of drones and flying birds, especially the identification, is still lacking effective technology and means [2]. The "black flight" is still very common.

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Once used by terrorists to carry dangerous weapons, it will seriously threaten public safety.

Both the drone and the bird are non-rigid targets. The rotation of the drone's rotor and the flapping of the bird's wings will introduce additional modulation sidebands near the Doppler frequency of the radar echo generated by the translation of the main body. It is called the micro-Doppler (m-D) effect. Due to the faster rotation speed of the UAV's rotor, its micro-motion period is much faster than that of the bird, but its strength is weaker than the bird's micro-Doppler [3, 4]. In addition, the irregular wing flapping caused by the bird's maneuvering makes the m-D feature more complex. The echo of the rotor drone is the superposition of the Doppler signals of the main body and the rotor components. The rotation of the rotor produces the modulation characteristics of the echo, which is time-varying and periodic, and has the characteristics of micro-motion. Different types and numbers of rotors are different. Therefore, the m-D characteristics are good solution for the classification of UAVs and flying birds and will improve the radar's fine description and recognition abilities of target motion.

At present, for the m-D feature recognition of targets, methods based on neural network algorithms show high recognition accuracy [5–7]. Compared with methods based on empirical mode decomposition (EMD), principal component analysis (PCA), and linear discriminant analysis, methods based on deep convolutional neural networks (DCNN) can directly learn and obtain effective features from the original data. It has received great attention in the field of pattern recognition and is widely used. CNN as an important part of deep learning, has been widely used in image recognition and classification [8]. It has two important properties, local connection and weight sharing, and can directly learn the image automatically and extract the features of the target, so as to realize the high-precision recognition of the image.

The current models based on CNN classification use the convolution operation of the convolution kernel and learn features from the information of the input layer according to the characteristics from coarse to fine. This kind of method is very easy to make the network model learn some useless feature information for multi-target motion states and complex environments, which will lead to over-fitting problem. And the generalization ability would become worse. Therefore, how to fully develop a feature information that can learn the target at a finer granularity, while retaining the useful feature information and suppressing the invalid feature information, will play an important role in improving the feature extraction and classification capabilities of complex moving targets.

In this paper, the classification of flying bird and rotary-wing UAV is analyzed based on the m-D features. Based on the K-band frequency-modulated continuous wave (FMCW) radar [9], the target micro-motion signal measurement experiment was carried out, and radar dataset was constructed. A multi-scale CNN model is proposed for the learning and classification of micro-movement features of different types of targets, which can extract global and local information of m-D features. The measured data verifies the effectiveness of the algorithm. Section 2 introduced the micro-motion measurement of drones and flying bird based on K-band FMCW radar. M-D classification of flying bird and UAV target via multi-scale CNN is introduced in detail in Sect. 3, including the CNN model structure, m-D classification method, and classification results analysis. The last section concludes the paper and presents its future research direction.

2 Micro-motion Measurement of Drones and Flying Bird Based on K-Band FMCW Radar

2.1 Description of K-Band FMCW Radar

When the FMCW radar is working, a voltage-controlled oscillator (VCO), a phase-locked loop (PLL) and a modulator together generate a FMCW signal, and then through a power divider or a coupler, a part of the generated signal is amplified and sent to the transmitting antenna and transmitted. The other part is sent to the mixer, where it is mixed with the received signal processed by the low-noise power amplifier to obtain the difference frequency signal. After the digital conversion, it is sent to the digital signal processing equipment for further processing. Finally, the digital signal processing equipment can calculate the relevant information of the difference frequency signal, including the frequency information and phase information of the signal, and then combine the modulation law of the signal to further obtain the target's distance, speed, azimuth and other information.

The K-band FMCW radar system used in this paper is mainly composed of four parts: radio frequency module, control module, acquisition module and software module. The radio frequency module realizes the transmission of FMCW signals, and mixes, filters and amplifies the received echo signals; the control module is responsible for receiving commands from the computer, generating control signals, and further filtering and amplifying the echo signals; the acquisition module is responsible for collecting echoes and transmitting the original echo signal to the computer; the software module completes the information display and the setting of the radar core parameters. The main technical parameters of the K-band FMCW radar are shown in Table 1.

Table 1. Main parameters of K-band FM continuous wave radar.

Parameters	Value
Working frequency	23.7 GHz
Modulation bandwidth	10 MHz–2000 MHz
Modulation period	0.2 ms–10 ms
Repetition frequency	100 Hz–5000 Hz
−3 db beam range	Azimuth: 16° Elevation: 12°
−10 db beam range	Azimuth: 30° Elevation: 20°

Figure 1 shows the data acquisition and signal processing flowchart of K-band FMCW radar. Firstly, set the working mode, system parameters, and processing parameters in turn. Then set the relevant parameters for m-D analysis (pulse number, time window, frequency window) according to the time-frequency method. By means of fast Fourier transformation (FFT), moving target indication (MTI), short-time Fourier transform (STFT) and other related processing methods, the one-dimensional range profile, range-pulse image, and time-frequency image are obtained. Then adjust the time-frequency parameters online and observe the time-frequency diagram of the target. If the result is not good as expected, readjust the radar parameters; otherwise start data collection.

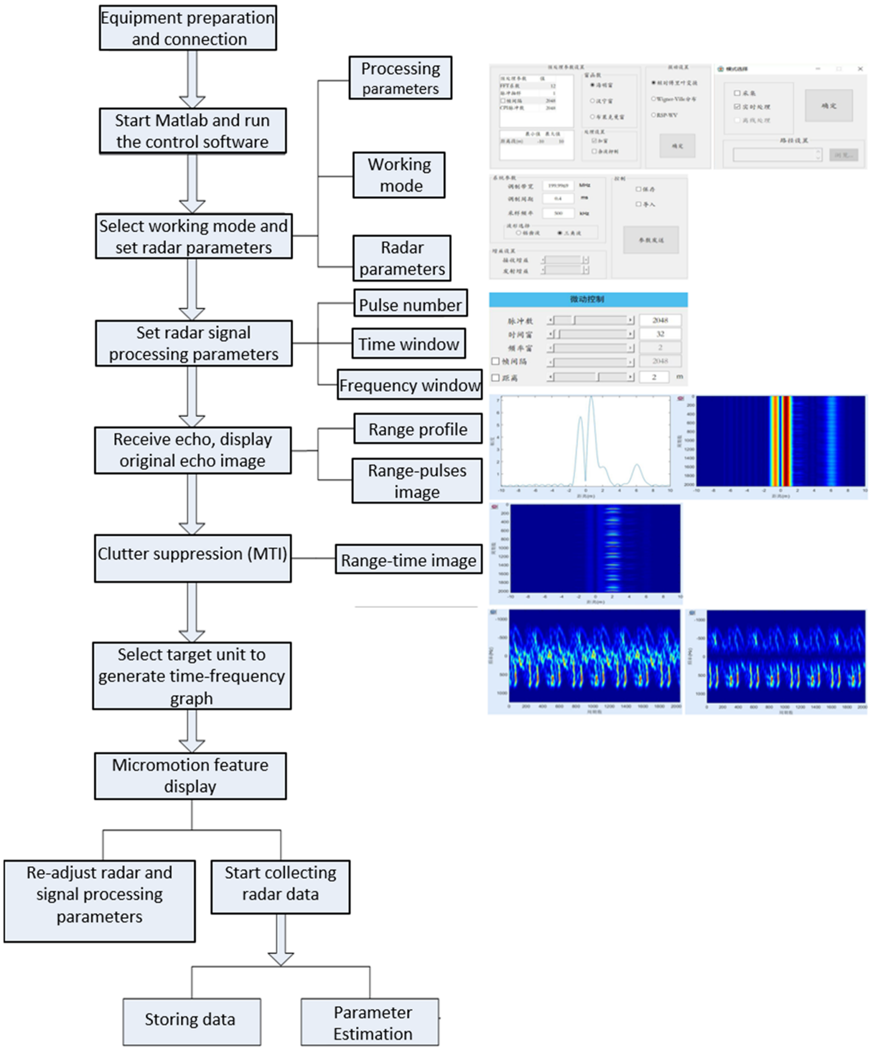
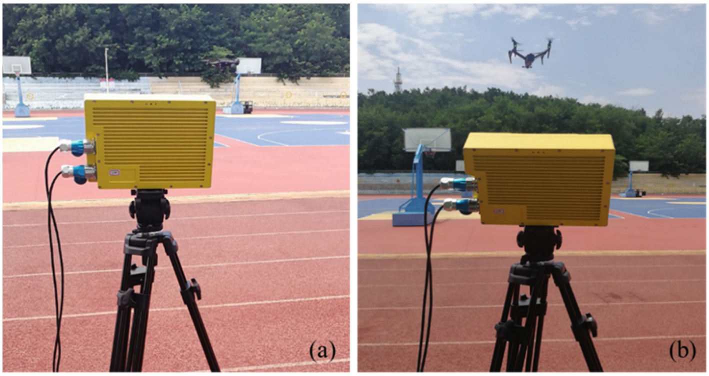


Fig. 1. Data acquisition and signal processing flowchart of K-band FMCW radar.

2.2 Data Collection and Micro-motion Analysis

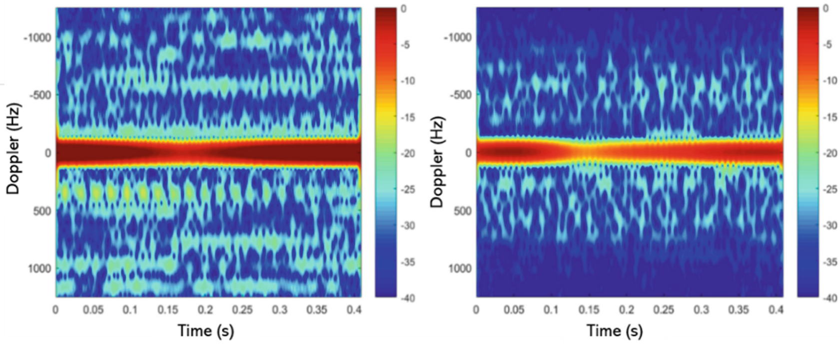
2.2.1 UAV Target Data Collection and M-D Analysis

The MAVIC Air 2 and Inspire 2 rotary-wing drones of DJI company were selected for the outdoor drone acquisition experiment, the experimental scene is shown in Fig. 2. The height of the drone and the distance of the radar are adjusted and the m-D features of real-time observation are carried out. Taking into account the relatively weak scattering characteristics of outdoor UAV rotor blades, clutter suppression may cause the loss of target information. Therefore, when analyzing the influencing factors of m-D characteristics, MTI clutter suppression processing is not performed on the echo signal. Figure 3 shows the m-D images of the two drone targets respectively. According to the measured m-D characteristic image of the rotor drone, it can be seen that the echo intensity at zero frequency and its surroundings is very strong. The m-D characteristics of the "Inspire 2" UAV have clearer m-D features than those of the "MAVIC Air 2" in Fig. 3(a).



(a) The MAVIC Air 2 (b) The Inspire 2

Fig. 2. Scene of drone experiment using FMCW Radar.

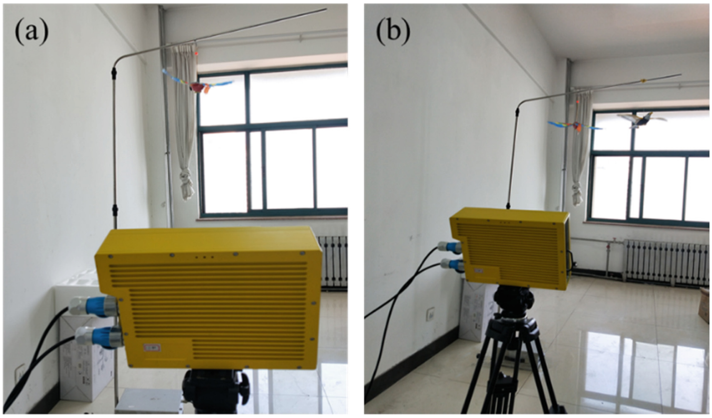


(a) The MAVIC Air 2 (b) The Inspire 2

Fig. 3. Micro-Doppler feature of different drone targets.

2.2.2 Flying Birds Data Collection and M-D Analysis

Due to seasonal influences, it is difficult to grasp the routines of flying birds, which makes the outdoor experiment more difficult. To solve this problem, this experiment uses a simulated bird that highly simulates the flapping flight of real birds. The subjects of the experiment are a single bird and two birds that perform flapping wings. The experimental scene of flying birds using FMCW radar is shown in Fig. 4.



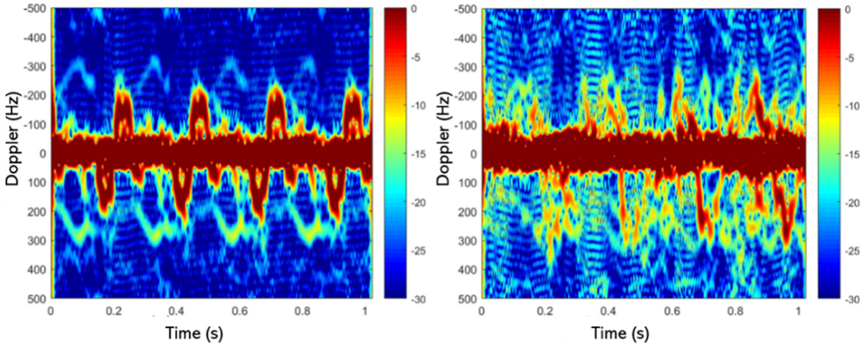
(a) Single simulated bird (b) Two simulated birds

Fig. 4. The experimental scene of flying birds using FMCW radar

The skeleton of the simulated bird used in the experiment is made of plastic, and the wings are made of cloth. Half wingspan $L = 42.0$ cm, swat frequency $f_{\text{flap}} = 3.5$ Hz. The parameters of the FMCW radar are set as follows: signal modulation bandwidth $B = 200$ MHz, sampling frequency (distance dimension) $f_s = 500$ kHz, carrier frequency is 23.7 GHz, signal modulation period is 1 ms, that is, the sampling frequency of periodic dimension is 1000 Hz. Number of cycles $N = 2048$, time window length is 32, observation distance $R = 2$ m, observation angle is 35°. As for the sampling frequency, the radar used in this experiment involves two sampling frequencies, one is the signal sampling frequency in the distance dimension (500 kHz), and the other is the signal sampling frequency in the periodic dimension (1000 Hz), which is equivalent to the pulse repetition frequency (PRF) in pulse radar. In the experiment, the m-D characteristics of the flapping wings of a single simulated bird and a pair of simulated birds are shown in Fig. 5 respectively.

In the time-frequency domain of the single-simulated bird, it can be found that m-D effect produced by flapping wings of bird can be effectively observed by the experimental radar. And according to the waveform frequency and Doppler peak data of the m-D characteristic in the figure, we can further estimate the wingspan length and swat frequency of the simulated bird. While from the time-frequency image of Fig. 5(b), it is found that when simulating the side-by-side flapping movement of two birds, the micro-motion characteristics in the time-frequency domain may be overlapped.

Based on the echo signal acquisition and feature extraction and analysis of the indoor simulated bird, the simulated bird experiment is brought to the outdoor environment for micro-motion signal acquisition. The simulated bird does not make any changes, only the radar parameters are appropriately adjusted. The signal modulation period is set to



(a) Micro-Doppler of a single simulated bird (b) Micro-Doppler of two simulated birds

Fig. 5. The micro-Doppler characteristics of the flapping wings of birds.

0.4 ms, the observation distance is 2 m, and other parameters remain unchanged. The obtained m-D characteristics of simulated bird flight are shown in Fig. 6. According to the time-frequency image, the m-D effect produced by the experimental radar on the flapping wings of birds can still be observed.

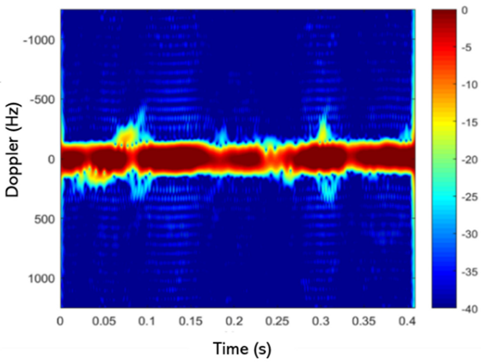


Fig. 6. Micro-Doppler characteristics of outdoor simulated birds.

3 Micro-doppler Classification of Flying Bird and UAV Target via Multi-scale CNN

3.1 Novel Multi-scale CNN Model

At present, for the target recognition methods based on m-D features, many CNN classification models are shallow structures, and cannot be applied in case of the smaller data samples or the complex signals. The target features cannot be effectively learned. This paper proposed a target m-D feature classification method based on a novel multi-scale CNN, which uses multi-scale splitting of the hybrid connection structure. The output of the multi-scale module contains a combination of different receptive field sizes, which is conducive to extracting the global feature information and the local information of the target.

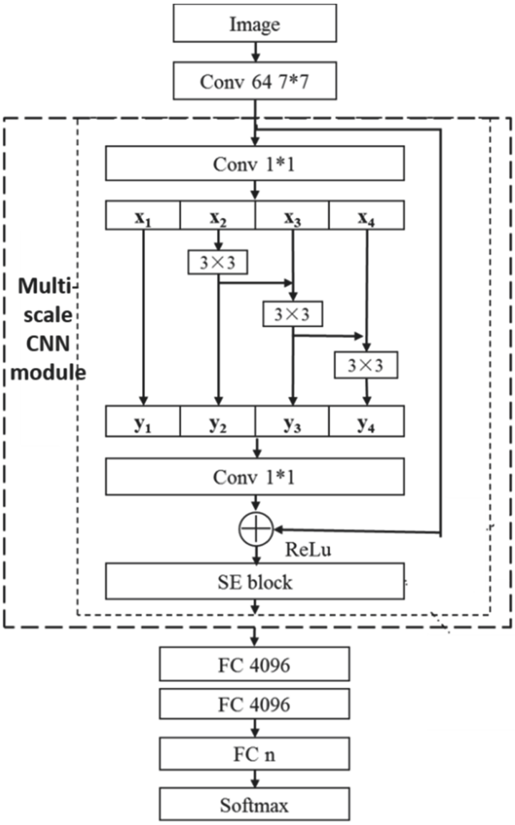


Fig. 7. The proposed multi-scale CNN model.

The structure of the novel multi-scale CNN model is shown in Fig. 7, which is based on the residual network module. The feature map after 1 × 1 convolution, assuming that there are *n* channels, replace *n* with a filter bank with a convolution kernel size of 3 × 3. The feature map after 1 × 1 convolution of two channels is divided into *s* feature map subsets, and each feature map subset contains *n*/*s* number of channels. Except for the first feature map subset that is directly passed down, the rest of the feature map subsets are followed by a convolutional layer with a convolution kernel size of 3 × 3, and the convolution operation is performed. The second feature map subset is convoluted, a new feature subset is formed and passed down in two lines. One line is passed down directly; and the other line is combined with the third feature map subset using a hierarchical arrangement connection method and sent to the convolution to form a new feature map subset. And then the new feature map subset is divided into two lines, one is directly passed down, and the other line is still connected with the fourth feature map subset using hierarchical progressive arrangement and sent to the convolutional layer to obtain another new feature map subsets. Repeat the above operations until all feature map subsets have been processed. Each feature map subset is combined with another feature map subset after passing through the convolutional layer. This operation makes the equivalent receptive field of each convolutional layer gradually increase, so as to complete the extraction of information at different scales.

Use $K_i()$ to represent the 3×3 output of the convolution kernel, and x_i represents the divided feature map subsets, where $i \in \{1, 2, ..., s\}$ and s represents the number of feature map subsets divided by the feature map. The above process can be expressed as follows

$$
\begin{aligned}
y_1 &= x_1 \\
y_2 &= K_2(x_2) \\
y_3 &= K_3(x_3 + y_2) = K_3(x_3 + K_2(x_2)) \\
y_4 &= K_4(x_4 + y_3) = K_4(x_4 + K_3(x_3 + K_2(x_2)))
\end{aligned}
\tag{1}
$$

Then the output y_i can be expressed as

$$
y_i = \begin{cases} x_i & i = 1; \\ K_i(x_i) & i = 2; \\ K_i(x_i + y_{i-1}) & 2 < i \leq s \end{cases}
\tag{2}
$$

According to the network structure and the above formula, it can be seen that this split hybrid connection structure can make the output of the multi-scale module include a combination of different receptive field sizes. This structure is beneficial to extracting global and local information. After the above-mentioned multi-scale structure is mixed and connected, the processed feature map subsets are combined by a splicing method, and then a convolutional layer with a convolution kernel size of 1×1 is used to fuse the spliced feature map subsets. Then the information fusion of s feature map subsets is realized. After that the multi-scale residual module is combined with the identity mapping $y = x$ to form a multi-scale residual module.

Finally, a three-layer fully connected layer is added after the multi-scale model structure. On the one hand, the effective features learned by the multi-scale model structure are mapped to the label space of the sample; the second advantage is to increase the depth of the network model so that it can learn more deeply hierarchical abstract features. Compared to the use of global average pooling, the fully connected layer can obtain faster convergence speed and higher recognition accuracy for the recognition of micro-motions.

3.2 Micro-motion Classification Method

This paper proposes a classification method for flying birds and rotary-wing UAVs based on the proposed multi-scale CNN structure. The flowchart is shown in Fig. 8, which is consisted of four parts, radar echo data processing, m-D dataset construction, model training and model testing.

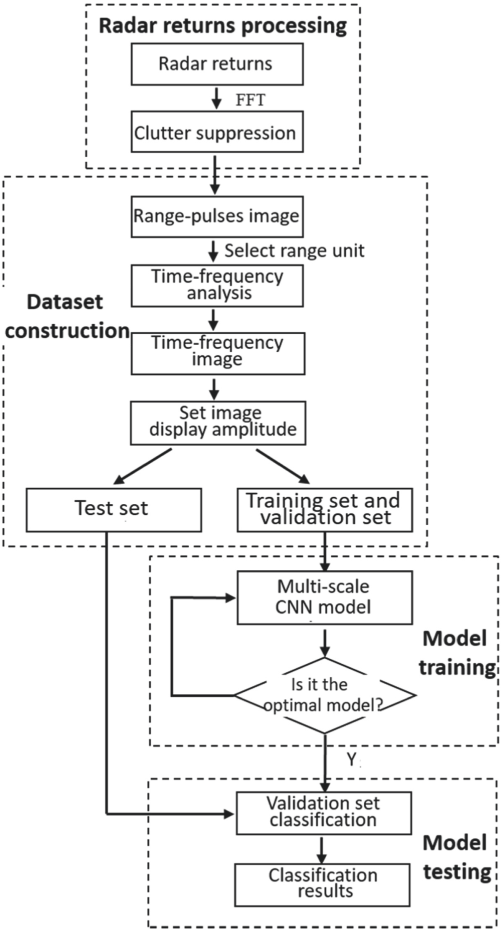


Fig. 8. Micro-motion classification flowchart of flying bird and UAV target.

Step 1: Radar echo data preprocessing. Fast Fourier transform (FFT) is used to obtain the Doppler spectrum of the target micro-motion for different ranges, and the MTI technology is used to perform pulse-to-pulse cancellation on the echo range-pulses data to obtain the echo data after clutter suppression.

Step 2: M-D dataset construction. Select the appropriate target range unit from the range-pulses profile, and use the time-frequency analysis method to extract the m-D features of the target to obtain the time-frequency image. The time-frequency image is reshaped for edge clipping and size normalization. The processed dataset is randomly divided into training data and test data, and the training data is divided into training set and validation set according to the preset ratio.

Step 3: CNN model training. Input the constructed time-frequency image dataset into the multi-scale CNN model for feature learning. The feature learning of the multi-scale

CNN model is to perform an iterative training on the training set, and then verify and analyze the network model on the verification set, and continuously optimize and adjust the network parameters until the expected recognition accuracy rate is reached on the verification set. At this time, the parameters of the multi-scale CNN model are saved, and the optimal network model is obtained.

Step 4: Target classification (Model testing). Input the test data not involved in training and verification into the optimal network model to verify the effectiveness and generalization ability of the multi-scale CNN model. The verification of the validity and generalization ability of the multi-scale CNN model is to calculate the ratio of the number of correctly classified samples of the test data set to the total number of samples in the entire test set. Finally the target classification results are obtained.

3.3 Classification Results Analysis

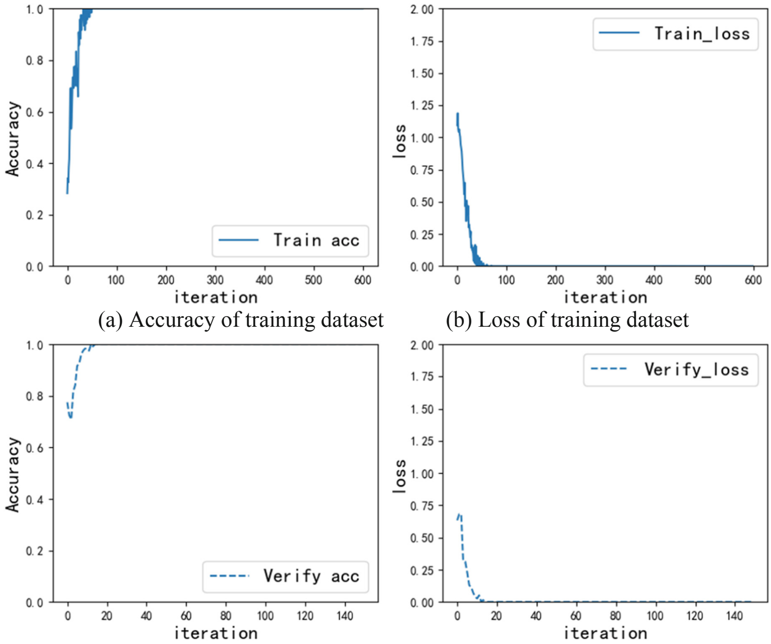
The dataset is composed of training data and test data. At the same time, the training data is randomly divided into training data set and verification data set according to the ratio of 8:2. The test data is composed of data that has not participated in training and verification, as shown in Table 2.

Table 2. Target recognition classification dataset composition.

Category	Training data	Testing data
Flying birds	900	69
Rotor UAV	900	69
Total	1800	138

The number of training is 50, the number of training batches is 120, and the number of iterations of the training set is 600 (($1440 \div 120) \times 50 = 600$), and the number of iterations of the validation set is 150. Based on the proposed multi-scale CNN network model, high recognition accuracy is obtained in the category recognition of flying birds and rotary-wing UAVs, as shown in Fig. 9. It is found that as the number of iterations increases, the classification accuracy rate quickly reaches 100% and remains unchanged, and the loss value is infinitely close to zero, indicating that the multi-scale CNN structure has fast convergence ability and high classification accuracy.

Finally, the generalization ability of the network model is verified on the test set, and the experimental results are shown in Table 3. It can be seen from the confusion matrix that the total recognition probability of the multi-scale network model can reach 99.51%, and the recognition probability of each target is not less than 98.55%. By analyzing the classification results, it is found that the rotation of the dual-rotor and dual-blade of the UAV is similar to the m-D features produced by the dual simulated bird flapping motion. Therefore, the network model is misjudged as the same category.



(a) Accuracy of training dataset
(b) Loss of training dataset
(c) Accuracy of validation dataset
(d) Loss of validation dataset

Fig. 9. Accuracy and loss of target recognition classification on training and validation sets

Table 3. Confusion matrix of classification result.

	Flying birds	Rotor UAV
Flying birds	100.0%	0
Rotor UAV	1.45%	98.55%

4 Conclusions

In this paper, the classification of flying bird and rotary-wing UAV is analyzed based on the m-D features. Based on the K-band FMCW radar, the target micro-motion signal measurement experiment was carried out, and radar dataset was constructed. A multi-scale CNN model is proposed for the learning and classification of micro-movement features of different types of targets, which can extract global and local information of m-D features. The measured data verifies the effectiveness of the algorithm. In the future, more radar detection experiment for different types of flying birds and rotor UAVs will carry out.

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