Moving Target Detection Classifier for Airborne Radar Using SqueezeNet

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Abstract. Conventional moving target detection methods for airborne radar always need many training range units. To solve this problem, this paper transforms the target detection problem into a multi-classification problem. Firstly, the training dataset is constructed based on a small amount of training range units. Then, a multi-class classifier based on SqueezeNet is constructed. Finally, the trained classifier is used to extract the characteristics of the received space-time data for target detection and parameter estimation. Simulation results show that the SqueezeNet-based airborne radar moving target detection method proposed in this paper can effectively detect the target and estimate its distance, doppler frequency, and other parameters. Compared with the conventional space time adaptive processing method, the proposed method can significantly reduce the number of needed training range units. Compared with the existing target detection method based on classification, the proposed method can effectively improve the accuracy of target detection and parameter estimation.

1. Introduction

When the airborne radar detects ground targets, the clutter signal intensity in the received echo is large, the Doppler spectrum is broadened and changes with the beam incidence angle. Conventional one-dimensional filtering technology such as Moving Target Indication (MTI) and Moving Target Detection (MTD) often cannot suppress clutter effectively. Scholars proposed to extend one-dimensional time domain filtering and spatial domain filtering to two-dimensional filtering combined with time domain and space domain, using Space Time Adaptive Processing (STAP) method to achieve adaptive clutter suppression and target detection [1].

In recent years, in order to reduce the computational complexity of the STAP method and the need for independent and identically distributed training range units, scholars have proposed practical STAP methods such as dimensionality reduction, rank reduction, and direct data domain [2]-[4]. Compared with the above methods, the moving target detection method based on pattern recognition does not need to estimate the clutter covariance matrix, and can use a small number of training range units to construct a classifier, process radar’s space-time echo data to detect target. Traditional pattern recognition-based moving target detection method needs to be further improved in the case of non-uniform clutter environment and low signal-to-clutter ratio due to the shallow structure of the constructed classifier and poor feature extraction ability [5],[6].

Deep learning technology can quickly and effectively extract deep-level features by training, summarizing and learning the acquired information, and has been widely used in many fields, providing new ideas for radar target detection [7]-[10]. Literature [11] uses AlexNet to construct a classifier to achieve effective detection of the target, and has better performance than the method in literature [5],[6].
However, the method proposed in [11] has problems such as many network parameters, slow calculation speed and unstable detection. In order to solve the defects of multiple parameters and slow speed, this paper constructs a classifier for airborne radar moving target detection based on SqueezeNet [12], which directly processes the received space-time echo data, and realizes target detection through classification and recognition.

2. Signal model & Dataset
The received signal of the radar from a moving target in one range unit includes two parts: signal coming from the moving target and the composite of clutter, jamming and noise. Assuming there are \( N_c \) clutter patches evenly distributed in the azimuth angle from 0 to 180 degree and no jamming signal [13], the radar received signal at the \( n \)-th array element corresponding to the \( m \)-th pulse can be represented as:

\[
x_{m,n} = x_{m,n}^T + x_{m,n}^C + \xi_{m,n} = \alpha_T e^{i2\pi (m-1)f_T' + (n-1)f_D'} + \sum_{i=1}^{N_c} \alpha_i e^{i2\pi (m-1)f_i' + (n-1)f_D'} + \xi_{m,n}
\]  

where the first term denotes the echo from the moving target signal, the second term denotes the echo from clutter and the third term denotes the noise in echo. \( m = 1, 2, ..., M \), \( M \) is the number of pulses transmitted in a coherent interval (CPI) and \( n = 1, 2, ..., N \), \( N \) is the number of array elements. \( \alpha_T \), \( f_T' \) and \( f_D' \) are the complex amplitude, the normalized space frequency and the normalized Doppler frequency of the moving target. \( \alpha_i \), \( f_i' \) and \( f_D' \) are the complex amplitude, the normalized space frequency and the normalized Doppler frequency of \( i \)-th clutter patch. \( \xi_{m,n} \) denotes the additive thermal noise.

A large dataset is needed to train proposed classifier built by convolutional neural network. The size of dataset is determined by three factors: the number of target categories, the number of different amplitudes and the number of training range units. \( K \) is the number of target categories which is related to the Doppler frequency or \( M \). \( P \) and \( Q \) are the number of amplitudes and the number of training range units respectively, which are set by ourselves.

3. Methods
We use Fire module of SqueezeNet to replace conventional convolution layer of AlexNet. The structure of Fire module is shown in Figure 1.

![Figure 1. The structure of Fire module](image-url)
Fire module consists of squeeze layer and expand layer, where squeeze layer uses 1*1 convolution and the expand layer uses 1*1 and 3*3 convolution in parallel. Parameters are reduced due to the use of small convolution kernel size.

The deep CNN architecture of the proposed CNN-MTI method by others based on AlexNet is shown in Figure 2. It is composed of four convolutional layers, two pooling layers, one fully connected layer and one final classification layer. We keep the first convolutional layer unchanged because there are few input channels, only two.

![Figure 2. the structure of AlexNet-based classifier](image)

### 4. Results

In this section, we generate training dataset through simulation to train our proposed SqueezeNet-based classifier and AlexNet-based classifier previously proposed by others. The parameters of training dataset are shown in Table 1. According to the parameters in Table 1, the size of training dataset is 13736, which is the product of the three parameters of $M$, $N$, and $Q$. The size of a single data is $M*N*2$, where 2 means that the two channels are the real and imaginary parts of the signal respectively. Parameters of Fire module in SqueezeNet-based classifier are shown in Table 2. The training process is realized via Tensorflow 2.1.0. The number of training epochs is set to 18, and the batch size is 16. The comparison between parameters and training time of the two classifiers is shown in Table 3. Total params of our proposed SqueezeNet-based classifier are much smaller than the previous AlexNet-based classifier so that it can be applied to hardware with limited memory. Correspondingly, the training time of our proposed SqueezeNet-based classifier is also shortened to 1/3 of the previous AlexNet-based classifier.

| Parameters | Values |
|------------|--------|
| $M$        | 16     |
| $N$        | 14     |
| $K$        | 17     |
| $P$        | 101    |
| $Q$        | 8      |
Table 2. parameters of Fire module in SqueezeNet-based classifier

| Parameters | Values |
|------------|--------|
| $s_1$      | 16     |
| $e_1, e_3$ | 32     |

Table 3. comparison of the two classifiers

|                  | Total params | accuracy  | Training time |
|------------------|--------------|-----------|---------------|
| AlexNet-based    | 457,905      | 99.60%    | 10m18s        |
| SqueezeNet-based | 20,897       | 99.75%    | 3m8s          |

We use the trained classifiers to detect the target, which is located in the middle of the 33 range units, corresponding to 9-th category. The detection results are shown in the Figure 3 and Figure 4.

In the detection results, the darkest color in each range unit means that this range unit has the greatest probability of identifying this category predicted by classifier. Ideally, only the range unit where the target is located is classified into the corresponding category, and the remaining range units are all category 0 because there is no target. We can see clearly from the test results that proposed SqueezeNet-based classifier is better than AlexNet-based classifier because of fewer misjudgments.

5. Conclusions
In this paper, we propose a classifier constructed based on SqueezeNet, which processes the space-time echo data received by the radar and realizes the detection of moving targets by extracting features. The simulation results show that compared with the traditional STAP method, this method can reduce the number of training range units; compared with the existing AlexNet-based target detection method, it has fewer parameters, faster speed and similar accuracy.

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