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Integrated Processing of Radar Detection and Classification for Moving Target via Time-frequency Graph and CNN Learning

Xiaolong Chen*, Ningyuan Su, Jian Guan, Xiaoqian Mou, and Yonghua Xue
Naval Aviation University, Yantai, China, 264001

1. Introduction

As the main means of target detection and surveillance, radar is widely used in the field of public safety and defense security. However, due to the complex environment and the complex motion characteristics of the target, the target echo is extremely weak and has low observability, which makes it difficult for the radar to detect the moving target in the clutter background [1]. The low-observable moving target detection in clutter has become a key constraint technology and a worldwide problem [2]. The traditional moving target detection (MTD) method is only applicable for uniformly moving targets. For the maneuvering targets under strong clutter and interference conditions, radar echoes will not meet the requirements of traditional signal processing. Moreover, the classification for different motions is difficult and not general under complex environment. There is an urgent need to develop and study adaptive, general and efficient methods for moving target detection and classification.

In recent years, with the rise and vigorous development of artificial intelligence, deep learning has been more and more widely studied and applied in the field of intelligent signal processing. Among them, convolutional neural network (CNN) has great advantages in image recognition and target detection [3]. Compared with traditional object detection feature extraction methods, e.g., scale-invariant feature transform (SEFT), and feature classification methods, e.g., support vector machine (SVM[4]), CNNs have better performances in features learning and expression. The CNN can automatically extract image features by convolution of kernel and images, thereby achieving high performances in target recognition and a high detection probability. Considering that the moving target echo can be modeled as a frequency modulated signal, an effective analysis can be performed using a time-frequency analysis method. After signal being converted into a time-frequency two-dimensional map, the deep learning network can be used for image processing, thereby completing the detection and classification of the moving target.

In this paper, a maritime target detection and classification method based on CNN is proposed. The time-frequency map of radar echo is classified by CNN to realize the differentiation of target and clutter. First, time-frequency analysis is performed on the IPIX [5] measured data to obtain time-frequency maps. Then the time-frequency maps are used to construct datasets, which is used for CNN training and testing. Based on the results of testing, we compare the target detection performance of different CNN models, and analyze the influence of sea states. Besides, use simulated echo signal of target and real measured sea clutter signal in IPIX data to build a dataset for target detection and classification. Finally test the CNN model with X-band CSIR radar data, which contains various kinds of real maritime target under sea clutter.

2. Descriptions of the CNN Models

In this paper, LeNet and GoogLeNet, which are commonly used in CNN, are selected for the simulation of maritime target detection and classification. A CNN is mainly consists of multiple convolution layers, pooling layers and fully connected layers, and finally uses softmax to classify and output.

2.1. CNN Models

A **LeNet** network consists of 7 layers (and an input layer). It consists of two convolution layers, two fully connected layers and one softmax output layer. Each convolution layer is followed by a pooling layer. The fully connected layer computes the dot product between the input vector and the weight vector, plus an offset, and the result is output through the sigmoid function.

$$S(x)=\frac{1}{1+\mathrm{e}^{-x}} \tag{1}$$

The output layer uses a radial basis function (RBF) as network connection.

$$y_i=\sum_j (x_j-w_{ij})^2 \tag{2}$$

The closer the RBF output value is to 0, the closer the recognition result is to the *i*-th category.
GoogLeNet, as is shown in Fig 1, is a convolutional neural network model built by increasing the depth and width of the network model. It consists of 22 layers with more than 100 parameters. It uses RGB tri-color channels and the size of the sensed

pixels is 224×224. To prevent the gradient from disappearing, it sets two loss functions of different depths to guarantee the return gradient. In order to avoid over-fitting and speed up the convergence, ReLU (Rectified linear unit) operations are performed after each convolution operation. It also increases the width of the network by using the inception module.

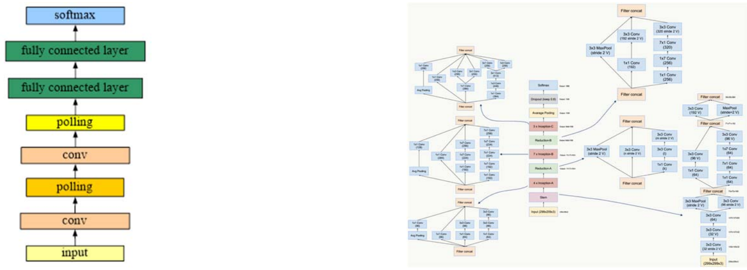


Fig. 1. Structure of LeNet (left) and GoogLeNet (right)

2.2. Model Training

This paper uses the architecture of Python2.7, VS2013, CUDA7.5, cudnn5.1, caffe, and the graphical interface processing of images by NVIDIA Digits, and the computer configuration includes a dual E5 processor, NVIDIA Quadro M2000 graphics card and a memory of 24GB. According to the convergence of loss value in the training process, choose stochastic gradient descent (SGD) as parameter solving algorithm. Initial learning rate is 0.01, with a change rate of 0.1 and a step size of 30%. The performance of network changes with the number of iterations done during training, which is shown in Fig 2.

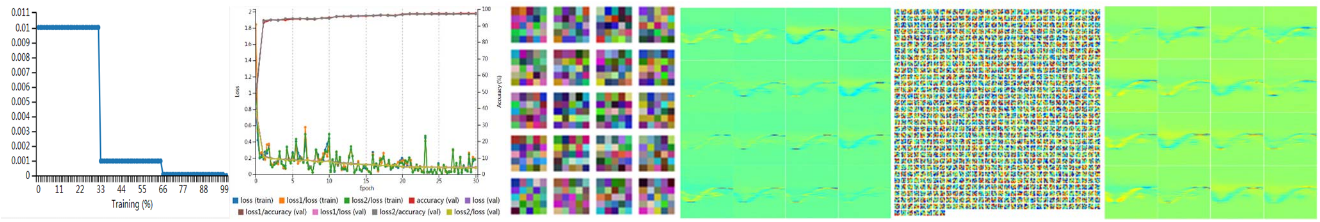


Fig. 2 learning rate line, model training, kernel of conv1, feature maps of conv1, kernel of conv2 and feature maps of conv2.

2.3. Simulation and Algorithm Flow

The algorithm flow mainly includes four parts: (1) data preprocessing (2) dataset construction (3) target detection (4)target classification, and the flow chart is shown in Fig 3. First, the radar echo is demodulated and pulse compressed. Next, the short-time Fourier Transform (STFT) is used to transform the echo signal into two-dimensional time-frequency maps containing moving target and sea clutter, which are used to construct training set and testing set. Then, the target detection is performed, the target detection model is trained tested by IPIX data, and the detection probability and the false alarm rate are obtained. The target classification model is trained by simulated target signal and tested by real measured target signal in CSIR data.

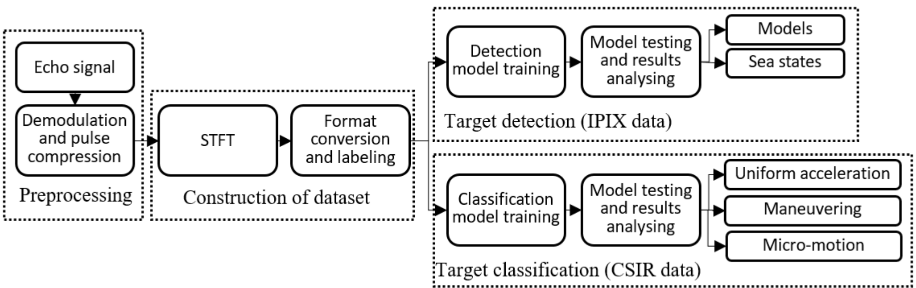


Fig. 3 The algorithm flow of integrated radar moving target detection and classification

3. Simulation and Analysis Based on IPIX and CSIR Data

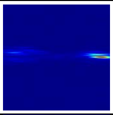
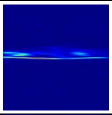
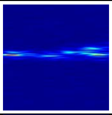
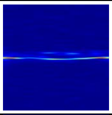
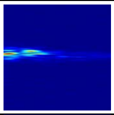
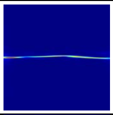
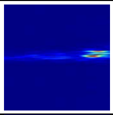
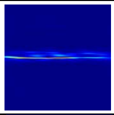
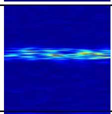
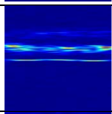
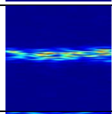
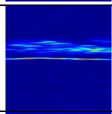
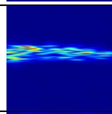
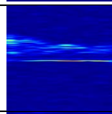
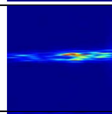
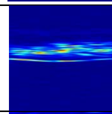
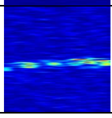
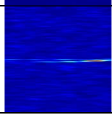
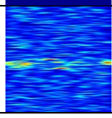
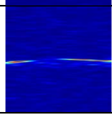
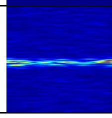
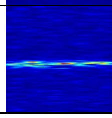
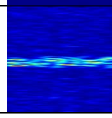
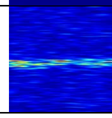
3.1. Dataset

This paper uses the standard measured data of sea clutter and targets collected by MacMaster University using IPIX [5] radar in the Dartmouth area of in Canada in 1989. The radar works in X-band (9.39GHz) and the pulse repetition frequency is 1000Hz. More detailed information about IPIX data can be obtained at website (soma.ece.mcmaster.ca). The data we use includes data collected under the level 2, 3, 4 sea states. The weather and sea state information and the descriptions are as follows:

Table 1. Weather and sea state information

Sea state	Temperature	Wave height	Wave period	Wind speed
Level 2	4.9℃	1.0m	5.5s	4m/s
Level 3	8.6℃	1.5m	5.2s	6m/s
Level 4	7.7℃	2.1m	8.2s	9m/s

Table 2. Examples of dataset

Polarization	HH		HV		VH		VV	
Label	Clutter	Target	Clutter	Target	Clutter	Target	Clutter	Target
Sea state level 2								
Sea state level 3								
Sea state level 4								

In IPIX data, the target is of low velocity. Under the level 2 sea state, the Doppler shift of clutter is small, and the spectra of clutter is overlap with that of target. Under the level 3 sea state, the clutter has a larger Doppler shift, making its spectra separated with target. Under the level 4 sea state, the clutter is close to Gaussian distribution and sea pikes are more dispersed

3.2. Analysis of Performance of Target Detection

In the simulation experiment of comparison of different detection models' performance, the data's signal polarization mode uses HH, and the training set consists of 9000 samples, including 4500 clutter samples and 4500 target samples. In each category, the samples collected under each sea state consists 1/3 of the dataset. 20% of the samples of training set are separated as validation set. The testing set consists of 3000 samples including 1500 clutter samples and 1500 target samples, and the samples collected under each sea state consists 1/3 of the dataset. Training and testing results are shown in the table 3. The results show that under the HH polarization mode, compared with LeNet, GoogLeNet has higher target detection performance under various sea conditions, with lower false alarm rate and higher detection probability.

Table 3. Results of detection of two models

Model	Detection probability	False alarm rate	Total Time
LeNet	91.06%	5.28%	195s
GoogLeNet	95.43%	4.37%	242s

According to the results above, the trained GoogLeNet model is used to test the dataset constructed by echo signals in different sea conditions. The testing set of each sea state contains 1500 target samples and 1500 clutter samples collected under the corresponding sea state. Besides, another simulation is carried out in which the samples of training data are collected under same sea state as those of testing data. The results are shown in the table 4. (1)When the training data are of same sea state: Under the level 2 sea state, the false alarm rate is the lowest, but the corresponding detection probability is also the lowest. The detection probability under level 3 and level 4 sea states are close to 100%, but the false alarm rate is also much higher. (2) By comparing the simulation results, it can be found that under high sea conditions, using the data of the same sea state to build training set and testing set can reduce the false alarm rate of target detection, which is maintain within 0.03.

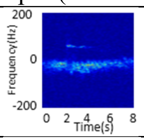
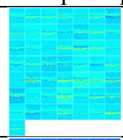
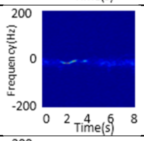
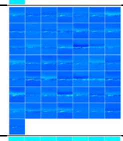
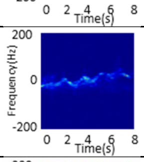
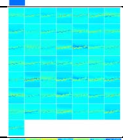
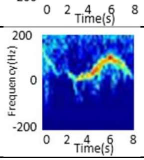
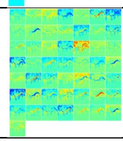
Table 4. Results of target detection under different sea states

Sea states of training data	Level 2,3,4	Level 2	Level 2,3,4	Level 3	Level 2,3,4	Level 4
Sea states of testing data	Level 2	Level 2	Level 3	Level 3	Level 4	Level 4
Detection probability	85.98%	88.11%	100.00%	100.00%	99.67%	95.55%
False alarm rate	1.86%	2.72%	8.04%	0.27%	5.05%	1.19%

3.3. Analysis of target classification model

The GoogLeNet is selected for the target classification model. Training dataset consists of 5120 simulated target samples, divided into four types: uniform acceleration, maneuvering, micro-motion I (violent) and micro-motion II (weak). The CSIR data, TFC17_006 (radar works in X-band, 9GHz, with a PRF of 5000Hz, http://www.csir.co.za/small_boat_detection), is used for the testing of the model. The performances are also compared with those of support vector machine (SVM) and some examples of sample testing are as follows.

Table 5. Results of target classification by CNN and SVM (correct judgement are in bold)

Sample (8seconds)	Type	Prediction by CNN		Feature maps of pool 2	Prediction by SVM
	Uniform acceleration	**Uniform acceleration**	**99.92%**		**Uniform acceleration**
		Maneuvering	0.0%		
		Micro-motion Ⅰ	0.08%		
		Micro-motion Ⅱ	0.0%		
	Maneuvering	Uniform acceleration	11.26%		Uniform acceleration
		Maneuvering	**49.20%**		
		Micro-motion Ⅰ	39.49%		
		Micro-motion Ⅱ	0.05%		
	Micro-motion Ⅰ	Uniform acceleration	0.01%		Uniform acceleration
		Maneuvering	0.0%		
		Micro-motion Ⅰ	**99.99%**		
		Micro-motion Ⅱ	0.0%		
	Micro-motion Ⅱ	Uniform acceleration	0.0%		Uniform acceleration
		Maneuvering	0.01%		
		Micro-motion Ⅰ	0.0%		
		Micro-motion Ⅱ	**99.99%**		

The results above shows that: (1) the maritime target can be detected by the method of deep learning and time-frequency analysis. Under the sea states of level 2, 3, 4, the detection probability exceeds 85.98%. (2) Training the models with samples collected under a certain sea state to adapt to certain environment can improve the performance of the model by reducing false alarm rate, especially under higher sea states. (3) Among the two models mentioned in this paper, LeNet is more efficient in radar echo processing, but GoogLeNet has better performance in terms of detecting probability and false alarm rate. (4) The results obtained in this paper are obviously worse than the results based on the simulation data. In addition to the diversity of the measured data itself, the targets' low speed and acceleration in IPIX data may also contribute to this difference. Under this circumstance, the Doppler spectrum of targets overlap with that of sea clutter. (5) CNN based method can be used to classify targets with different motion states by analyzing their radar echo and has better performances in classification than SVM.

4. Conclusion

This paper proposed a maritime target detection and classification method based on CNN. The results reflect the high-precision and intelligent advantages of CNN in target and clutter feature extraction and recognition. CNN also have advantages in the classification of targets with different motion states. Next, study of judgment criteria, simulation process optimization and study of other measured data will be carried out.

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