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A Classification Method of Ship Radiated Noise Based on Simulation Signal of Variational Auto-Encoder

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Abstract. The performance of the classifier is weak when the number of the ship radiated noise samples is insufficient. Aiming at above problem, this paper proposes a classification method of ship radiated noise based on simulation signal of variational auto-encoder (VAE). First, build a VAE model, input the real ship radiated noise signals into the model to generate a large number of VAE simulation signals. Then, extract the typical features of simulation signals, and use these features to pretrain a convolutional neural network (CNN) classification model. Finally extract the typical features of the real signals to be predicted, and use the pretrained CNN to complete the classification. Experimental results show that the classification accuracy of the pretrained CNN model is 6% to 12% higher than that of the non-pretrained CNN model.

Keywords. Ship target classification; small sample; variational auto-encoder; convolutional neural network.

1. Introduction

Accurately classify ship radiated noise is of great significance to the maintenance of maritime territorial security. The traditional ship radiated noise classification task is very dependent on the role of sonar soldiers [1, 2]. But the accuracy of the discrimination will be affected by the physiological as well as psychological factors of the sonar soldiers [3]. So the reliability of this method is very weak. With the rapid development of neural networks, the underwater target classification technology based on deep learning has been developed rapidly. In recent years, classifiers based on neural network models have achieved better classification and recognition results than humans [4]. But training a neural network model with excellent classification effect requires a large number of training set samples. However, the collection cost of ship radiated noise is very high, so there are few samples. Therefore, the neural network model has poor classification performance.

In view of the insufficient number of samples, some people [5, 6] use generative adversarial networks (GAN) to expand the LOFAR spectrogram of the signal, after that use CNN for classification. But this method does not make good use of all the information of the signal, so the accuracy needs to be improved. Based on this, this paper proposes a classification method of ship radiated noise based on simulation signals. This method uses a VAE model to generate a large number of simulation signals. Then we use those to solve the task of target classification when there are few samples. Finally, this method effectively improves the classification accuracy of the CNN model.



The rest of this article is organized as follows. In section 2, we build a VAE model based on ship radiated noise to generate simulation signals. In section 3, we build a CNN model, and then extract the characteristics of the simulated signal to train as well as optimize the model. In section 4, we use the pretrained CNN model to classify real signals. At the same time, we compare the classification performance of the non-pretrained model. Finally, conclusions are summarized in section 5.

2. Establishment of VAE Model Based on Ship Radiated Noise Signal

2.1. The Establishment of VAE Model

Due to the high cost of collecting ship radiated noise signals, the existing data set samples are few. However, the neural network-based classifier requires a large number of dataset samples to be trained to obtain better classification performance [7]. Therefore, this paper uses a VAE model [8] to generate the simulation signals of ship radiated noise.

The VAE model consists of two parts: Encoder and Decoder [9], both of which have 4 hidden layers. In the Encoder, the first and fourth layers are fully connected layers, while the second as well as third layers are convolutional layers. The structure of the Decoder is similar to that of the Encoder. In the Decoder, the first as well as fourth layers are fully connected layers, but the second and third layers are deconvolution layers. Their first three hidden layers all contain ReLU nonlinear activation functions. In addition, the convolutional layer of Encoder consists maximum pooling. In the Encoder part, the input is a small batch of real signals. After full connection, dimension upgrade, convolution, dimensionality reduction and full connection operations, it output the mean and logarithmic variance of samples. While in the Decoder stage, the input is a random sample taken from a certain distribution. After full connection, dimension upgrade, deconvolution, dimensionality reduction, and full connection, it output simulation signals. In this paper, the input samples of the Decoder obey the standard normal distribution. In other words, the input samples are Gaussian white noise. The VAE model is shown in figure 1.

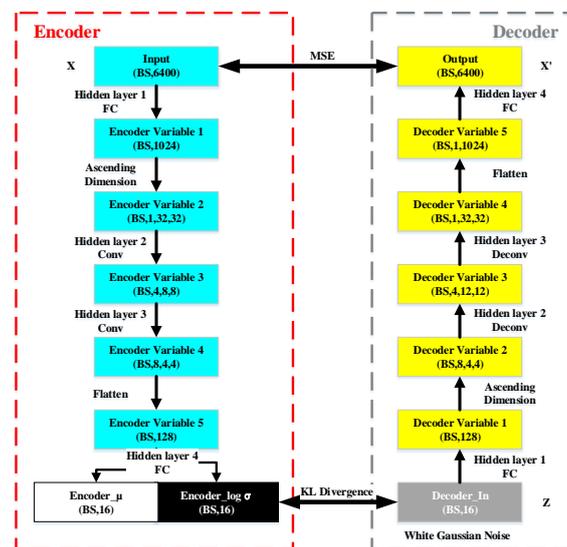


Figure 1. Structure of VAE model.

2.2. Optimize VAE Model to Generate Simulation Signal

The loss function of the VAE model contains two items: reconstruction loss as well as distribution loss. The reconstruction loss measures the difference between the generated simulation signals and the input real signal. The distribution loss measures the difference between the probability distribution of

random noise which is entered into the Decoder and the probability distribution of the mean value and logarithmic variance from the Encoder output.

The basic idea of using the VAE model to generate simulation signals is as follows. First, input the real signals into the VAE model, but limit the output of the VAE model according to the constraints of reconstruction loss as well as distribution loss. So that the generated simulation signals obey the same probability distribution, at the same time having the key information of real signals. Here, the reconstruction loss is calculated using MSE, while the distribution loss is calculated using KL divergence [10], which can be expressed as equations (1) and (2).

$$Loss_{MSE}(X', X) = \frac{1}{N} \sum_{i=1}^N (x'(t) - x(t))^2 \tag{1}$$

$$Loss_{KL}(p | q) = \int p(x) \log\left(\frac{p(x)}{q(x)}\right) dx \tag{2}$$

Among them, $x(t)$ and $x'(t)$ are real signal and simulation signal, while X and X' are their sets respectively. $p(x)$ and $q(x)$ are respectively the probability distribution that the output of the Encoder obeys as well as standard normal distribution.

Figures 2 and 3 show the reconstruction loss and distribution loss when the VAE model generates the second type of simulation signals. It can be observed that the VAE model tends to converge after 500 epochs.

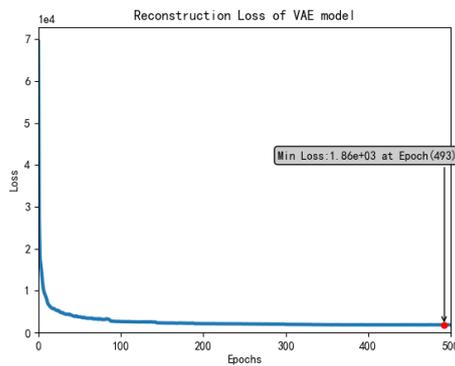


Figure 2. Reconstruction loss of VAE.

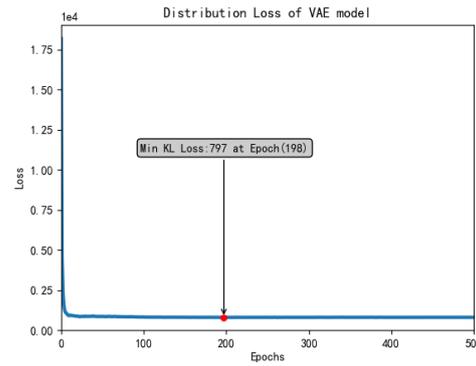


Figure 3. Distribution loss of VAE.

We have three types of ship radiated noise samples, while the number of each type is between 700 and 1,100. Now we use the VAE model to generate 10000 simulation signals for each type of signal, so the dataset samples are expanded. In the next section, we will use these samples to train a convolutional neural network.

3. Use Simulation Signals to Train And Optimize the CNN Classification Model

3.1. Build the CNN Classification Model

Benefiting from its deep network model structure, deep learning can make classification decisions based on the characteristic information of samples. Compared with the fully connected neural network, CNN can learn more deeply the characteristics of samples. Therefore, this paper builds a CNN classification model with 5 hidden layers. The first 3 hidden layers are all convolutional layers, while the last 2 layers are fully connected layers. Each convolutional layer contains convolution operations, batch normalization, nonlinear activation and pooling filters. The convolution operation is shown in equation (3).

$$Y_d = \sum_{d=1}^{D-1} (X_d * W_d) + b_d \tag{3}$$

Among them, D is the dimension of the input feature, X_d is the input matrix, and W_d is the convolution kernel matrix. Convolution operation is represented by *. Bias is replaced by b_d .

Non-linear activation is included in the fourth fully connected layer. The non-linear activation functions in this paper all use the ReLU activation function, and its calculation formula is shown in equation (4). The operation of the neurons in the fully connected layer is shown in equation (5).

$$y = \sigma(x) = \max(0, x) \tag{4}$$

$$y = \sigma\left(\sum_{i=1}^{N-1} (x_i \cdot w_{i,j}) + b_j\right) \tag{5}$$

Among them, x represents the value of the input neuron, while y represents the output of the neuron. $y = \sigma(\cdot)$ represents non-linear activation. $w_{i,j}$ represents the weight value between the input signal x_i and neuron j. In addition b_j represents the internal bias of neuron j.

Finally, the CNN classification model built in this paper is shown in figure 4.

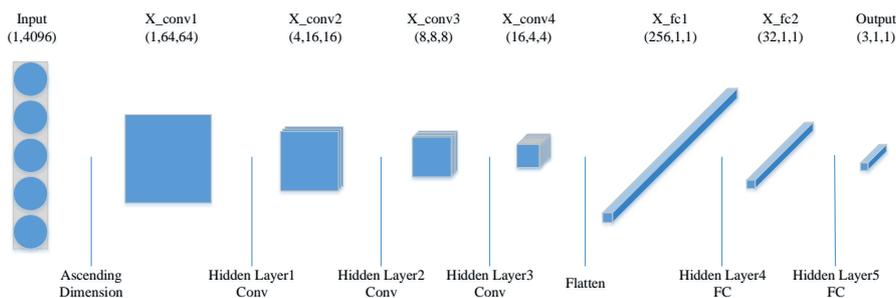


Figure 4. CNN classification model.

3.2. Use Simulation Signals to Pretrain a CNN Model

In the marine environment with low signal-to-noise ratio, the low-frequency line spectrum of ship radiated noise is easily masked by background noise. The DEMON [11] feature could obtain the invariable physical characteristics of the ship. We first extract the DEMON feature of the simulation signals, and then use those to train and optimize the CNN model. The specific implementation steps are shown in table 1.

Table 1. Steps to pretrain the CNN model using simulation signals.

Step1: According to the ratio of 7:3, randomly divide the simulation signal samples into training set and validation set.
Step2: Extract the DEMON feature of the datasets.
Step3: Use samples of training set to train the CNN classification model.
Step4: Dynamically adjust the learning rate of the network according to the classification accuracy of the samples in the validation set to achieve better classification results.
Step5: Save the optimized CNN classification model.

The classification performance of the simulation signals on the CNN model are shown in figures 5 and 6.

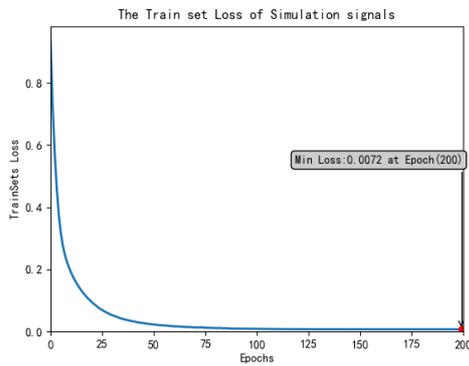


Figure 5. Training set loss of simulation signal features.

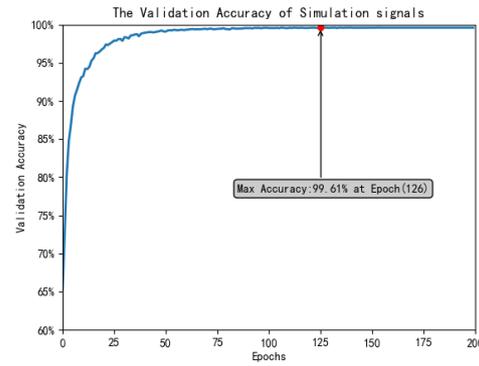


Figure 6. Validation set classification accuracy of simulation signal features.

It is very obvious from the figures that the classification accuracy of simulation signals on the validation set is very high, which has exceeded 99%. Therefore, the CNN model that we pretrained with simulation signals has strong reliability.

4. Classification and Discrimination of Real Signals

First, according to the ratio of 7:2:1, we divide the characteristic dataset samples of the real signals into the training set, validation set and test set. Then we use transfer learning [12] to transfer the parameters of the pretrained CNN model. The specific implementation steps are shown in table 2.

Table 2. Steps to classify real signals using the pretrained CNN model.

- Step1: Load the pretrained CNN model in section 3.
- Step2: Freeze the first four hidden layers of the pretrained CNN model, and change the parameters of the last hidden layer only.
- Step3: Fine-tune the pretrained CNN model using the training set samples of the real signals.
- Step4: Adjust the neuron parameters of the last layer according to the classification accuracy of the validation, so that get a better classification accuracy.
- Step5: Use the test set samples to test the classification performance of the CNN model, after that save the results.

Then, we use a non-pretrained CNN model as well as the pretrained CNN model to classify real signals. The accuracy on the validation during the training process is shown in figure 7. Next, we test the pretrained CNN model on the test set of real signals, so the confusion matrix is shown in figure 8.

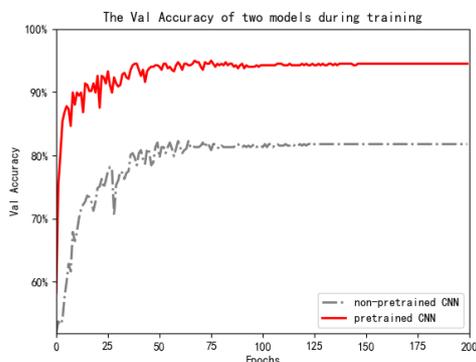


Figure 7. Confusion matrix on the test set of the pretrained CNN model.

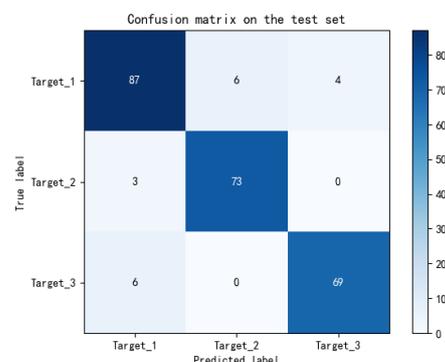


Figure 8. Accuracy on the validation set of two CNN models during training process.

It is very obvious from the figure 7 that the accuracy on the validation set of pretrained CNN is about 10% higher than that of the non-pretrained CNN. It shows that the pretrained CNN is effective.

Finally, we compare the classification accuracy of the two CNN models on the test set. The comparison results are shown in table 3.

Table 3. Classification performance of two CNN models on the test set.

Model	Target 1 Accuracy	Target 2 Accuracy	Target 3 Accuracy
Non-pretrained CNN	81.44%	89.47%	80.00%
Pretrained CNN	89.69%	96.05%	92.00%

From table 3, we could intuitively observe that compared to the non-pretrained CNN model, the classification accuracy of the pretrained CNN model on the test set has increased by 6% to 12%. It shows that the CNN model pretrained by simulation signals has better performance in classification tasks than the non-pretrained CNN model.

5. Conclusions

This paper proposes a classification method of ship radiated noise based on simulation signals. First, we construct a VAE model to generate a large number of simulation signals, namely the simulation signal dataset. Then, we build a CNN classification model. Next, we extract the features of simulation signals and real signals, after that train the CNN model using simulation signals. Besides, we use transfer learning to apply the pretrained CNN model to the classification task of the real signals. In the end, we compare the classification accuracy of the pretrained CNN model with that of the non-pretrained CNN model. The experimental results show that the classification accuracy of the test set of the pretrained CNN is increased by 6% to 12% compared with the non-pretrained CNN. The classification method proposed in this paper can be applied to target classification and recognition tasks in urban waters and oceans. But this method also has certain shortcomings. It takes a while to adjust the parameters when training the VAE model. In the follow-up work, we will reduce the optimization time of the algorithm in order to meet the requirements of real-time data processing.

Acknowledgments

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