Progress In Electromagnetics Research Letters, Vol. 112, 103–110, 2023

LFM Signal Sources Classification Based on Self-Supervised Learning

Tianqi Yang[1] and Siya Mi[1, 2, *]

Abstract—Linear Frequency Modulation (LFM) signals are widely used in radar and sonar technology. Many applications are interested in determining the source of an LFM signal. In recent years, the rapid development of machine learning has facilitated research in various fields, including signal recognition. The neural networks can extract the implicit features of the signals, which can help the system to sort and recognize the signal sources quickly and accurately. High performance of neural networks requires large amounts of high-quality labeled data. However, it is difficult and expensive to obtain a large amount of high-quality labeled data. Simultaneously, some features will be lost during data preprocessing, and feature extraction and classification tasks will be inefficient. The self-supervised network is proposed in this paper for pre-training the signal waveform and fine-tuning the classification with a small amount of labeled data. The proposed method can extract more signal waveform features, save labeling costs, and has higher precision. This method can provide up to 99.7% recognition accuracy at 20 dB.

1. INTRODUCTION

Linear Frequency Modulation (LFM) is a type of spread spectrum modulation technique that does not require a pseudorandom code sequence. LFM signals are frequently employed in wireless communication, sonar, and radar technologies due to their broad temporal breadth and bandwidth [1]. It is of great significance to the identification of LFM signal sources, and it has been paid attention to by people for a long time [2]. The traditional signal source identification methods are based on conventional features such as pulse width, pulse amplitude, and angle of arrival. With the increasingly complex electromagnetic environment, traditional methods based on inter-pulse parameters are difficult to distinguish signal sources [3]. The intra-pulse feature is one of the most useful features of radar signals, which can provide better stability and selectability.

The intra-pulse modulation features are the inherent features of the radar transmission signals and contain more features of the transmitter, which includes intentional modulation feature and fingerprint feature. For identifying the signal sources, wavelet packet feature, similarity coefficient, complexity, bispectral feature, and entropy feature are the most commonly used intra-pulse parameters [4]. The complexity and dynamic changes of intra-pulse features can be expressed more comprehensively in time-frequency domain. Therefore, in this paper, the received signal is analyzed in the time-frequency domain. Signal features with high degree of separation are extracted to complete the recognition and classification of signal sources. Typical time-frequency analysis methods include Short-Time Fourier Transform, Wavelet Transform, Choi-Williams Distribution Transform, and others [5]. In [6], a hybrid classification method is proposed using distance profile (RP) and time-frequency images. Short-time Fourier transform (STFT) is used to construct time-frequency images from the phase information of range-compressed signals. Then the data is filtered by RP, and the time-frequency images corresponding to the filtered data are used for classification. The classification of 6 signal sources can be achieved as

Received 31 July 2023, Accepted 13 September 2023, Scheduled 25 September 2023
* Corresponding author: Siya Mi (SiyaMi@seu.edu.cn).
[1] School of Cyber Science and Engineering, Southeast University, China. [2] Purple Mountain Laboratories, Nanjing, Jiangsu, China.

high as 92% accuracy at the signal-to-noise ratio (SNR) of 0 dB, by using the time-frequency images. In [7], the Choi-Williams distribution transform is employed to construct time-frequency images for nine types of low probability of intercept (LPI) radar signals. The denoised time-frequency images are utilized for feature extraction, and a softmax classifier is employed for signal classification.

In recent years, with the development of artificial intelligence, deep neural networks have been introduced into the field of radar radiation source recognition [8]. The published works reveal that better recognition performance can be achieved by neural networks than traditional methods, and the recognition accuracy can be as high as 100% under high SNR conditions. In [9], a Convolutional Neural Network (CNN) is constructed. Radar echoes are processed to generate bispectrum images. The dataset is constructed using data augmentation techniques such as image flipping and random cropping. Three signal sources are classified with up to 96% accuracy using this method, and better robustness and generalization than traditional methods. Similarly, in [10], one-dimensional convolutional networks are also used to complete signal source classification tasks. The difference is that the signal waveforms are used for training. The classification of 8 types of signal sources can reach 100% accuracy at the SNR of -10 dB. However, expensive labeled data is needed for supervised networks, and they are not suited for handling complex tasks.

In this paper, the self-supervised network is proposed for pre-training the signal waveform and fine-tuning the classification with a small amount of labeled data. This method is used to compensate the defects of traditional signal recognition in the complex electromagnetic environment and to optimize the deep learning method for signal source recognition. Compared with the time-frequency images, the signal waveform contains more abundant information, rather than just the static pixel values. Specifically, multiple feature dimensions are incorporated in time series data, including the features in temporal, spatial and frequency. More features can be extracted for identifying. Moreover, the proposed method does not require large amounts of high-quality labeled data, and avoids the need for manual preprocessing and feature extraction. Additionally, more features of the signal waveform are retained, which is more conducive to the downstream task of signal source recognition and classification.

This article is organized as follows. Section 2 introduces the model architecture including an introduction to the objective function. Section 3 introduces the setup of the experiment. Section 4 provides the experimental procedure and discusses the experimental results. Finally, the primary content of this paper is summarized in Section 5.

2. MODEL ARCHITECTURE

2.1. Self-Supervised Model

The self-supervised learning is primarily categorized into three types: context-based self-supervised learning, time-series task-based self-supervised learning, and contrastive-based self-supervised learning. The contrastive-based self-supervised learning is to compare a sample with other samples to construct a self-supervised task, so that the learned feature representation is easier to distinguish under a certain metric. In [11], a contrastive-based self-supervised model is utilized, and a new objective function is proposed. This function measures the cross-correlation matrix between the outputs of two identical networks and makes it as close as possible to the identity matrix. In this way, the same features are extracted across different inputs, and the redundancy between vectors is minimized. The contrastive-based self-supervised model is mostly used in image classification tasks. Therefore, the LFM signal needs to be trained in the form of a time-frequency image obtained through time-frequency transformations. Due to the process of time-frequency transformation, there is inevitable uncertainty between time and frequency. Some details of the original signal may be lost in the conversion process, especially for some high-frequency or rapidly changing signals. Thus, accurate signal representation and feature extraction may be affected.

A self-supervised network model for the signal waveform is proposed in this paper. The model makes LFM signals represented more accurately, and the loss of signal waveform features can be reduced. The network flowchart is depicted in Fig. 1.

The valid pulse waveform X is fed into this model and first passes through the multi-layer convolutional feature encoder $f : X \mapsto Z$ to extract features. The feature encoder consists of seven blocks, each containing 1D convolutions, layer normalization [12], and GELU activation function [13].

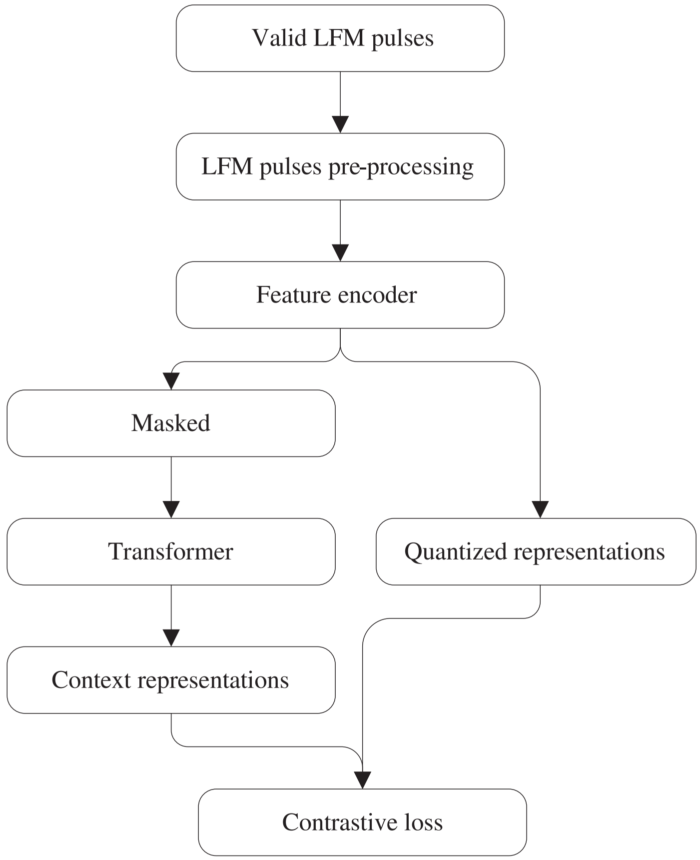

Figure 1. The flow chart of self-supervised network.

Then, the feature encoder output Z is fed into a context network $h : Z \mapsto C$ which follows the transformer architecture [14, 15]. At the same time, Z can be limited in a finite set Q through the quantization module $Z \mapsto Q$, and Q is used as the target of the predicted value C.

2.2. Objective Function

In the pre-training process, the representation of the signal waveform is learned by solving the contrast task L_1. The task requires the recognition of the true quantized signal representation among a set of interference terms in the presence of masking. The diversity loss L_2 is also referenced to enhance the training objective function. The output obtained by the feature encoder is squared and then averaged as L_3. The weighted sum of the three losses is used as the objective function for training:

$$L = L_1 + \gamma L_2 + \delta L_3 \tag{1}$$

The contrastive loss is calculated from the results of prediction and quantization. The output Z_t of the feature encoder is masked and then fed into the context network to get the prediction C_t. The model needs to recognize q_t which is quantized from Z_t, among $k+1$ quantized candidate representations $\tilde{q} \in Q_t$. q_t and k interference terms are included in Q_t. The interference terms are sampled from the quantized vectors of the same signal according to a uniform distribution. Contrast loss is defined as:

$$L_1 = -\log \frac{\exp(sim(c_t, q_t)/k)}{\sum\limits_{\tilde{q} \sim \mathcal{Q}_i} \exp(sim(c_t, \tilde{q})/k)} \tag{2}$$

where $sim(a, b) = \mathbf{a}^\top b/\|a\|\|b\|$ represents the cosine similarity between contextual representation and quantized vector.

The goal of diversity loss is to increase the number of quantized representations. The diversity loss is defined as:

$$L_2 = 1 - \frac{\sum_{g=1}^{G} \exp(-\sum_{v=1}^{V} p_{g\nu} \log p_{g\nu})}{GV} \tag{3}$$

where G is the given number of sets. Each set has V choices.

2.3. Fine-Tuning

For the above trained self-supervised network model, the feature encoder module is frozen, and a Multilayer Perceptron (MLP) with random initialization parameters is added. Only one hidden layer is contained in the MLP. The backbone network of the pre-trained model is frozen so that effective transfer learning can be achieved, especially in cases where the pre-training task is related to the fine-tuning task. Only the MLP needs to be trained, which makes the fine-tuning process more efficient. The information learned by a pre-trained model acts as a form of regularization during fine-tuning, which reduces the risk of overfitting on new tasks. The cross-entropy loss function is used to calculate the loss value of the model during the training process. Finally, the classification layer is fine-tuned using a small amount of labeled data. The weights of the MLP are gradually adjusted, which makes it better adapted to the target classification task.

3. EXPERIMENTAL SETUP

3.1. Data Preprocessing

The LFM signal is the most widely used waveform, because its waveform is easy to generate. The LFM signal is widely used for pulse compression in radar systems. The pulse signal is periodic, and each LFM signal has multiple valid pulse signals and invalid signals, so it is necessary to preprocess the sampled LFM signal. The effective pulse signal is extracted as a sample, and it is fed into the neural network.

To extract the valid signal, it is necessary to frame the LFM signal first. The total length of the LFM signal is N. Each frame is initialized with frame length L and frame shift l. The total number of frames of the sampled signal is denoted as N_f.

$$N_f = \frac{N - L + l}{l} = \frac{N - L}{l} + 1 \tag{4}$$

The product $EZ(i)$ of the short-time energy $E(i)$ and the zero-crossing rate $Z(i)$ is beneficial to extract every valid signal exactly. The starting position of the valid pulse can be obtained by setting an appropriate threshold according to $EZ(i)$. The calculation is as:

$$E(i) = \sum_{n=1}^{N} [x(i-1)N + n]^2 \tag{5}$$

$$Z(i) = 0.5 \sum_{1}^{N-1} |sgn(x(i-1)N + n + 1) - sgn(x(i-1)N + n)| \tag{6}$$

$$EZ(i) = E(i)^* Z(i) \tag{7}$$

where $sgn(x)$ is a symbolic function ($sgn(x) = 1$ for $x \geq 0$ and $sgn(x) = -1$ for $x \leq 0$).

This method is more accurate in extracting valid signals than using only short time energy or zero crossing rate [16]. Each valid signal is used as a training sample for the neural network. The valid signals of the same signal source are taken as one category. The process of extracting each valid pulse from the sampled LFM signal is described in Algorithm 1.

Algorithm 1 Extract effective signal algorithm

Require: Y_t, LFM signal obtained by sampling; N, Total length of sampled signal.
Ensure: {Initialization}
Set the number of Mel filters, $N_p = 20$;
Set frame length, $L_f = 160$;
Set frame interval, $L_i = 80$;
Divide the frames to get the number of frames, N_f;
Signal after framing, X_t;
X_t after normalization, X_m;
for $i = 1 : N_f$ **do**
    Calculate the short-term energy and get $E(i)$;
    Calculate the zero-crossing rate and get $Z(i)$;
    Calculate the product of short-time energy and zero-crossing rate, $EZ(i)$;
end for
Store the starting position of the valid signal, $p = [\,]$;
for $i = 1 : 2$: size of p **do**
    Valid signal $X_t = Y_t(p(i), p(i+1))$;
end for

3.2. Training Method

The pulse signal is fed to the proposed self-supervised model, and features are obtained through the feature encoder. The next feature value is predicted by the contextual representation module based on several input feature values. Information leakage may occur in this process. The true values of the predicted feature might be accessed by the model during prediction. The prediction process is simplified in that case, making pre-training meaningless. In order to avoid information leakage, feature values are masked according to a certain proportion. This process is similar to masked speech modeling in BERT [17]. Based on the input features, the true value of the masked feature is identified by the model from a set of distractors. After pre-training, the feature encoding module is frozen, and MLP with random initialization parameters is added. The model is fine-tuned using a small amount of labeled data to complete the signal source classification.

4. EXPERIMENT AND DISCUSSION OF RESULTS

The LFM signals typically consist of three states: initial transient, steady-state, and ending transient. In this paper, the LFM signal is analyzed as a entirety without distinguishing between transient and steady states. Fig. 2 shows a partially sampled analog signal, including valid and invalid signals.

The data used in the experiment is 9 LFM analog signals with the same modulation mode. Each LFM signal contains 2000 pulse signals. 1500 pulse signals are randomly selected to feed into the self-supervised network, and the remaining 500 pulse signals are marked for fine-tuning the network parameters. The data used to fine-tune the network is divided into training and test datasets in a 5 : 1 ratio. The length of each pulse signal is 95200. The maximum length of valid pulses helps the self-supervised network learn more abstract features. The learning rate is set to 0.001. The batch size is 8, and the training is performed for 100 epochs.

In this paper, accuracy represents the proportion of correctly predicted samples out of the total number of samples in a classification task. The loss value is the difference between the model's prediction and the true label. It is used to measure the degree of fit of the model on the training and test datasets. A lower loss value indicates the model's prediction is closer to the true label. The generalization ability of the model can be evaluated based on accuracy and loss value.

After the valid pulse signal is segmented from the LFM signal, the method in Section 2 is used to complete the feature extraction. With a simple fine-tuning, the signal source recognition can be well completed. Fig. 3 shows the change of classification accuracy in the fine-tuning process. The results show that the features extracted by the self-supervised network can accurately recognize different signal

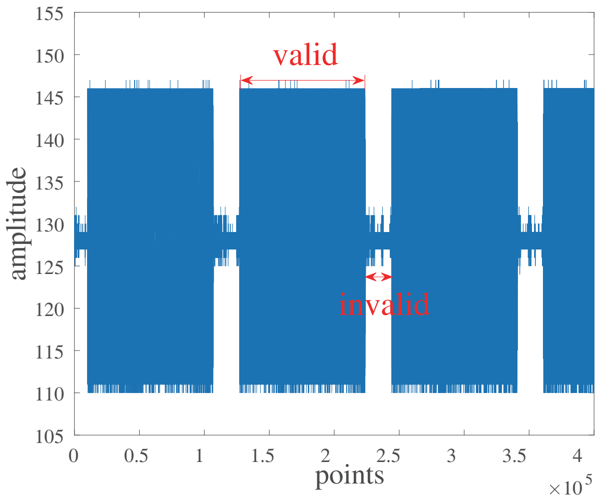

Figure 2. LFM sampling signal.

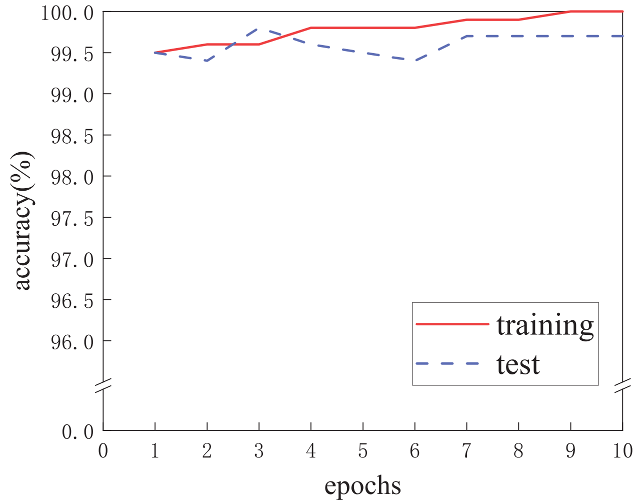

Figure 3. The change of classification accuracy.

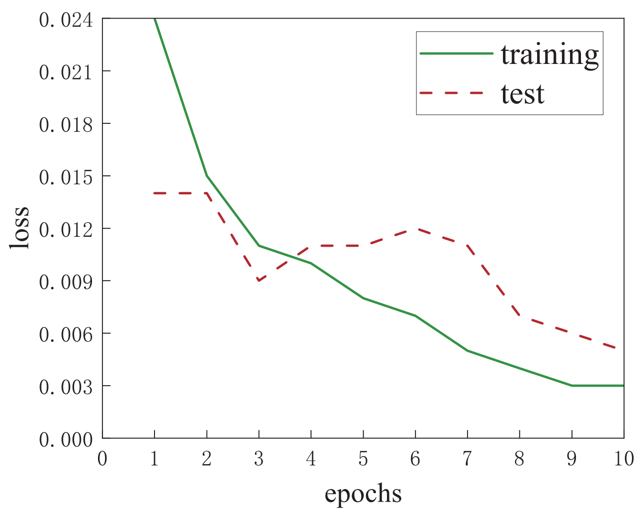

Figure 4. The change of loss value.

sources after fine-tuning with a small amount of labeled data. The classification task is accomplished more efficiently by this model. After the first epoch of fine-tuning, the accuracy reaches as high as 99.5%. With ten epochs of fine-tuning, the accuracy stabilizes at 99.7%. In Fig. 4, the loss value decreases during the fine-tuning process on both the training and test datasets, demonstrating the model's strong generalization ability.

Table 1 lists the comparison results between the proposed method and other methods used for waveform classification. From the comparison, it can be observed that the proposed method provides high accuracy for recognizing LFM signal sources. Moreover, identified categories is used more, and the labeled data is required less.

In general, the method proposed in this paper has a high recognition and classification effect on LFM signals. This method also perfectly solves the problem of feature loss in time-frequency images and the cost of a large amount of labeled data. Moreover, data without labels can be trained by the self-supervised model, avoiding the waste of data resources. The proposed model outperforms traditional methods and supervised learning with higher accuracy, efficiency, and generalization.

Table 1. The recognition accuracy of different methods.

model	category	acc(%)
CNN1 [18]	11	94.00
DNN [19]	7	100.00
BP & RBF [20]	6	94.17
CNN2 [21]	7	97.70
Proposed Classifier	**9**	**99.70**

5. CONCLUSION

A classification method based on self-supervised learning is proposed for LFM signal in this paper. The self-supervised network is used to pre-train signal waveforms and fine-tune classification with a small amount of labeled data. The proposed method can extract more signal waveform features and save labeling costs. Based on the general features obtained by self-supervised learning, the network is slightly adjusted according to the specific classification task. The convergence speed of the model is accelerated on the target task. Experimental results show that compared with other signal source classification methods, the proposed method can save labeling costs while ensuring high classification accuracy. The efficiency and accuracy of the model classification are improved.

ACKNOWLEDGMENT

This work was supported by the National Natural Science Foundation of China (62201146), Zhishan Scholar Program of Southeast University, and the Purple Mountain Laboratories, Nanjing, China.

REFERENCES

1. Galushko, V., "On application of taper windows for sidelobe suppression in LFM pulse compression," *Progress In Electromagnetics Research C*, Vol. 107, 259–271, 2021.
2. Guo, Y. and L. Yang, "Method for parameter estimation of LFM signal and its application," *IET Signal Process*, Vol. 13, No. 5, 538–543, 2019.
3. Li, H., Y. Han, Y. Cai, et al., "Overview of the crucial technology research for radar signal sorting," *Systems Engineering and Electronics*, Vol. 27, No. 12, 2035–2040, 2005.
4. Zhang, M., L. Liu, and M. Diao, "LPI radar waveform recognition based on time-frequency distribution," *Sensors*, Vol. 16, No. 10, 1682, 2016.
5. Wang, S., C. Cao, X. Li, et al., "Intra-pulse modulation feature analysis for radar signals," *Recent Trends in Intelligent Computing, Communication and Devices: Proceedings of ICCD 2018, Springer Singapore*, 819–825, 2020.
6. Han, S., H. Kim, S. Park, et al., "Efficient radar target recognition using a combination of range profile and time-frequency analysis," *Progress In Electromagnetics Research*, Vol. 108, 131–140, 2010.
7. Li, M., "Electronic radar signal recognition based on wavelet transform and convolutional neural network," *2022 2nd Asia-Pacific Conference on Communications Technology and Computer Science (ACCTCS), IEEE*, 470–474, 2022.
8. Gao, Z., F. Cao, C. He, et al., "Network optimization algorithm for radar active jamming identification based on neural architecture search," *Progress In Electromagnetics Research C*, Vol. 126, 183–196, 2022.
9. Zhu, H. and Q. Li, "Target classification by conventional radar based on bispectrum and deep CNN," *Progress In Electromagnetics Research C*, Vol. 130, 127–138, 2023.

10. Yildirim, A. and S. Kiranyaz, "1D convolutional neural networks versus automatic classifiers for known LPI radar signals under white gaussian noise," *IEEE Access*, Vol. 8, 180534–180543, 2020.
11. Zbontar, J., L. Jing, I. Mistra, etval., "Barlow twins: Self-supervised learning via redundancy reduction," *[12]International Conference on Machine Learning, PMLR*, 2021.
12. Ba, J., J. Kiros, and G. Hinton, "Layer normalization," *arXiv preprint arXiv:1607.06450*, 2016.
13. Hendrycks, D. and K. Gimpel, "Gaussian error linear units (gelus)," *arXiv preprint arXiv:1606.08415*, 2016.
14. Mohamed, A., D. Okhonko, and L. Zettlemoyer, "Transformers with convolutional context for ASR," *arXiv preprint arXiv:1904.11660*, 2019.
15. Baevski, A., M. Auli, and A. Mohamed, "Effectiveness of self-supervised pre-training for speech recognition," *arXiv preprint arXiv:1911.03912*, 2019.
16. Alimuradov, A. and A. Tychkov, "EMD-based method to improve the efficiency of speech/pause segmentation," *2021 International Siberian Conference on Control and Communications (SIBCON), IEEE*, 1–10, 2021.
17. Devlin, J., M. Chang, K. Lee, et al., "Bert: Pre-training of deep bidirectional transformers for language understanding," *arXiv preprint arXiv:1810.04805*, 2018.
18. O'Shea, T. J., J. Corgan, and T. Clancy, "Convolutional radio modulation recognition networks," *Engineering Applications of Neural Networks: 17th International Conference, EANN 2016*, 213–226, Springer International Publishing, Aberdeen, UK, September 2–5, 2016.
19. Fredieu, C., A. Martone, and R. Buehrer, "Open-set classification of common waveforms using a deep feed-forward network and binary isolation forest models," *2022 IEEE Wireless Communications and Networking Conference (WCNC), IEEE*, 2022.
20. Cunxiang, X., Z. Limin, and Z. Zhaogen, "Quasi-LFM radar waveform recognition based on fractional Fourier transform and time-frequency analysis," *Journal of Systems Engineering and Electronics*, Vol. 32, No. 5, 1130–1142, 2021.
21. Li, Y., G. Shao, and B. Wang, "Automatic modulation classification based on bispectrum and CNN," *2019 IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), IEEE*, 311–316, 2019.