

Channel-Robust Specific Emitter Identification Based on Transformer

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Abstract. Specific emitter identification (SEI) refers to the process of identifying emitter individuals based on corresponding wireless signals. Although deep learning has been successfully applied in SEI, the performance remains to be improved when the channel changes. In this paper, we suggest that a potential reason of the performance degradation is inadequacy of model capacity. Therefore, Transformer, an advanced neural network architecture with large model capacity, is applied for channel-robust SEI. Experimental results show that Transformer achieves better performance than conventional convolutional neural networks.

Keywords: Specific Emitter Identification, Transformer, Robust Classification.

1. Introduction

Specific emitter identification (SEI) is the process of identifying wireless devices from their radio frequency (RF) emissions [1]. SEI is feasible due to the fact that the electronic circuits of emitters possess specific characteristics, which are determined by the production and manufacturing processes [2]. As these physical-layer characteristics are independent of the content of signals, SEI has been widely applied for wireless security in both military [3] civilian fields [4].

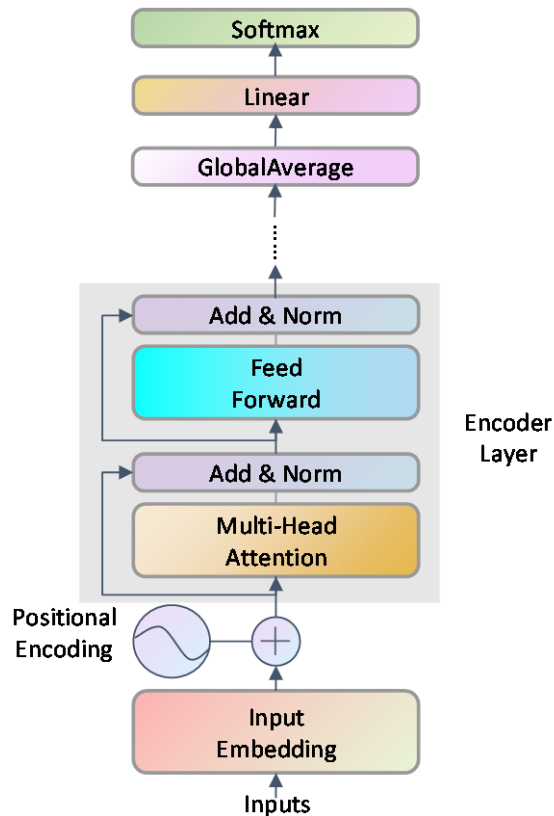


Fig. 1 Architecture of Transformer for SEI.

In recent years, deep learning methods have been extensively applied for SEI. Neural networks including recurrent neural network (RNN) and convolutional neural network (CNN) are utilized. For

example, long-short term memory (LSTM), a typical architecture of RNN, is adopted for SEI in [5, 6]. CNNs are employed for SEI in [7-11]. Despite the fact that deep learning methods have achieved superior performance for SEI when the training and testing data are received under the same condition, performance degrades when the testing data is received under a different condition. In particular, when the test data is received under the channel different from training data, the performance can degrade dramatically if not considered properly [12]. Data augmentation is an effective way to alleviate performance degradation caused by channel variations [12]. The idea behind the method is to simulate signals of different channels by augmenting training data. However, data augmentation can enhance the difficulty to train the network, and networks with limited capacity cannot classify emitter individuals effectively.

In this paper, an SEI approach based on Transformer is proposed to improve the performance under varying channels. Transformer is an advanced network architecture based on self-attention mechanism, which is able to capture long-range relations and hence possesses large capacity. To the best of our knowledge, this is the first attempt to apply Transformer for the task of SEI. Experimental results show that the proposed method achieves better performance than conventional deep learning methods when the channel of testing data is changed.

2. Problem Formulation

Define the ideal equivalent baseband signal transmitted by emitters as $s(t)$, then the received signal considering emitter characteristics is formulated as:

$$r(t) = h(t) * f_k(s(t)) + n(t), k \in [1, 2, \dots, K] \quad (1)$$

where $f_k(\cdot)$ is a function denoting the characteristics of the k th emitter and K is the number of emitters for classification. $h(t)$ denotes the channel impulse response, and $n(t)$ indicates additive white Gaussian noise. Samples are obtained by sampling from $r(t)$:

$$x[n] = r(t_0 + nT) \quad (2)$$

where T is the sampling period.

In this paper, we consider the situation when the channel of testing data is different from training data, i.e., $h_{train}(t) \neq h_{test}(t)$. The change of channels can lead to obvious performance degradation. In [12], data augmentation is utilized to achieve channel-resilient SEI:

$$r_{train}(t) = h_{aug}(t) * (h_{train}(t) * f_k(s(t))) + n(t) \quad (3)$$

where $h_{aug}(t)$ is random channel impulse responses for data augmentation by training on signals augmented by artificial channel responses, the neural network is able to generalize on testing data of unknown channels. However, data augmentation may improve the difficulty of training, and hence the neural network cannot learn discriminative features for different emitters.

3. SEI Based on Transformer

In this paper, we propose an SEI approach based on Transformer [13], which is capable of capturing long-range relations and has large learning capacity. Architecture of the Transformer network used in this paper is shown in Fig. 2.

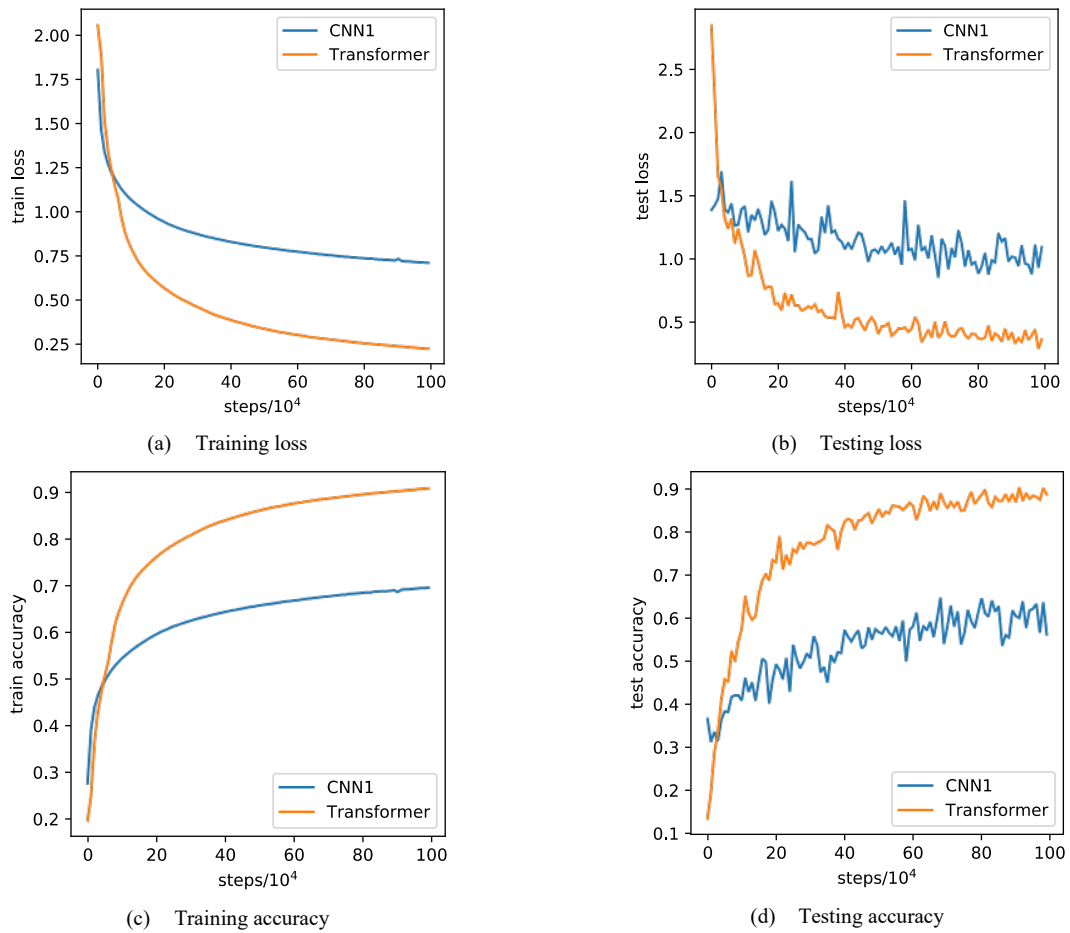


Fig. 2 Training and testing curves of CNN1 and Transformer with SNR=20dB.

The input signal is first added by positional encodings, then passed through multiple layers of encoder layers, and finally averaged and fed into a linear layer with Softmax activation, which outputs the prediction. Each encoder layer consists of a multi-head attention layer and a feed forward layer. One difference from the typical Transformer network is that no decoder layer is used, because the network performs classification task for SEI. Another modification is that layer normalization is replaced by batch normalization to mitigate the effect of outlier values in signals, as suggested by [14].

The input of the network is of shape $[B, 2, N]$, where B denotes the batch size, 2 implies that the input contains in-phase and quadrature-phase components, and N indicates the number of sampling points of each sample. The input embedding is a fully connected layer turning the input shape from $[B, 2, N]$ to $[B, D, N]$, where D is the dimension of Transformer. The positional encoding is the same as [13], which injects the absolute position information. In each encoder layer, the multi-head attention layer fuses information of different positions, while the feed forward layer fuses information of different dimensions. Then the global average layer averages values of all positions to turn the shape of input from $[B, D, N]$ to $[B, D]$, so that each sample is represented by a feature vector of dimension D . Finally, the linear layer with Softmax turns the shape from $[B, D]$ to $[B, K]$, which gives the probability of each sample belonging to each emitter.

4. Experiments

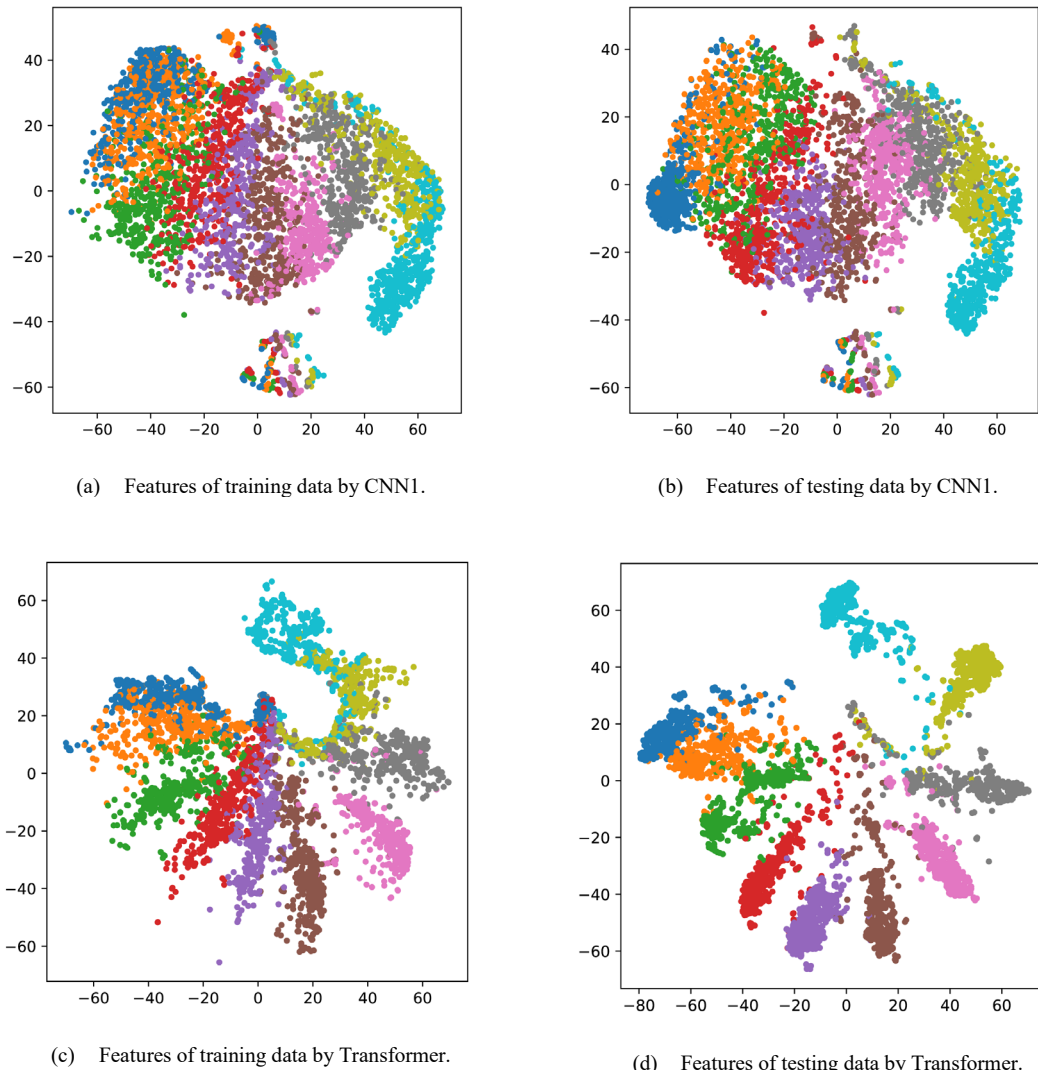


Fig. 3 Visualization of features learned by CNN1 and Transformer with SNR=20dB.

To evaluate performance of the proposed approach for SEI under channel changing conditions, the dataset provided by [12] is used as the benchmark. The dataset contains signals of 10 emitters under 2 channel conditions (Day1 and Day2). Signals of each emitter and each channel condition are collected under 16 different signal to noise (SNR) levels, in the range of -10dB to 20dB with steps of 2dB. The number of sampling points of each sample is $N=198$. The samples of Day1 are used as training data and the samples of Day2 are used as testing data. We use the same data augmentation method as described in [12].

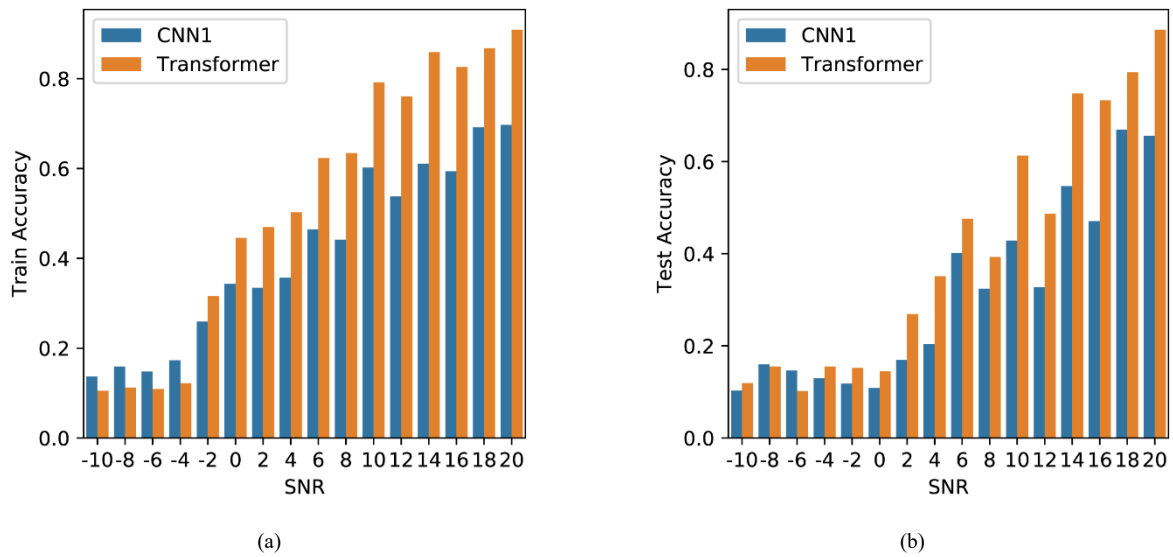


Fig. 4 Comparison of training accuracy and testing accuracy at different SNRs.

Transformer used for the experiment contains 5 encoder layers, and the dimension is set as $D=512$. We compare the proposed Transformer network with the CNN1 model proposed in [12]. Both networks are trained with batch size $B=512$, using Adam optimizer at learning rate of 10^{-4} for 10^6 steps.

The training and testing curves when $\text{SNR}=20\text{dB}$ are shown in Fig 2. Benefitting from large learning capacity, Transformer achieves lower training loss and higher training accuracy compared to CNN1. The testing loss and testing accuracy of Transformer is also more desirable than CNN1, implying that Transformer can generalize considerably for SEI.

The features learned by CNN1 and Transformer are visualized using t-SNE [15], as shown in Fig. 3. Different colors correspond to different emitters. Due to lack of learning capacity and disability to capture long-range relations, CNN1 cannot learn features that are evidently discriminative for different emitters. On the contrary, features learned by Transformer are more discriminative, proving the superiority of Transformer.

Accuracies under different SNRs are shown in Fig. 4. When $\text{SNR} \geq 0\text{dB}$, both training accuracy and testing accuracy of Transformer are higher than those of CNN1. When $\text{SNR} < 0\text{dB}$, accuracies of both CNN1 and Transformer are low due to the intense noises and the comparison is meaningless. Therefore, Transformer performs better than CNN1 at different SNRs.

5. Conclusion

In this paper, we propose a channel-robust SEI approach based on Transformer, which achieves substantial improvement over conventional CNN based methods, especially under channel-changing conditions. Transformer has the advantage of capturing long-range information and is able to learn complex patterns. Experimental results show that Transformer can learn more discriminative features from augmented data and achieves higher accuracy than CNN at different SNRs.

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