Recognizing Automatic Link Establishment Behaviors of a Short-Wave Radio Station by an Improved Unidimensional DenseNet

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ABSTRACT
It is difficult to recognize Automatic Link Establishment (ALE) behaviors of a short-wave radio station, if we do not acquire the radio station’s communication protocol standard. A method is proposed to recognize different ALE behaviors by using an improved unidimensional DenseNet. In this work, we directly recognize ALE signals in physical layer without the radio station’s communication protocol standard. Hence, we can avoid difficulties in demodulation, decryption and so on. Actually, the original DenseNet is used extensively in the field of computer vision, so the original DenseNet is firstly adapted for the unidimensional input. And then, two parallel dense blocks are used in our improved unidimensional DenseNet, which could improve the capability of network to extract ALE signals’ deep features. The experimental results show that the proposed method is able to recognize different ALE behaviors of a short-wave radio station. And improved DenseNet has better recognition performance than simple DenseNet. The simple DenseNet only contains one dense block. Finally, the results of comparison experiments also show that some classic networks have worse performance in ALE behaviors recognition, such as LeNet-5, ResNet-34, and DenseNet-121.

INDEX TERMS
Recognition, unidimensional DenseNet, automatic link establishment, short-wave radio station, electronic countermeasure.

I. INTRODUCTION
The ALE behaviors of a short-wave radio station include Call, Handshake, Notification, Time Offset, Group Time Broadcast, Broadcast and Scanning Call. The Link Establishment (LE) behaviors recognition of a short-wave radio station is important and difficult in the field of electronic countermeasures. Mastering the ALE behaviors of enemy’s radio station can effectively infer the communication intention and working status of the radio station in the wireless communication network. It provides a reference for further inferring the topological structure and tactical position of the short-wave radio station. As a reconnoiter in the field of electronic countermeasures, our goal is to recognize a radio station’s ALE behaviors without the radio station’s communication protocol (MIL-STD-188-141B) [1]. In this work, the purpose of ALE behaviors recognition is achieved by directly analyzing the signals in physical layer, avoiding the difficulties of demodulation and decryption during signal processing.

Whether at home or abroad, the research on the link establishment behaviors of radio stations is mostly based on the analysis of communication protocols [2]. It is a novel method to analyze the ALE behaviors of a radio station directly by recognizing signals in physical layer. The link establishment behaviors of a short-wave radio station belong to communication behaviors. Liu et al. [3], [4] can accurately find the communication relationship between wireless radio stations from the monitored physical layer signals, and there is no need to crack the information carried by signals. Xiang et al. [5] proposed an algorithm to mine command information flow under the condition that communication information is unknown between nodes in the communication network.

Under the demand of intelligent reconnaissance, the research on radio station’s ALE behaviors recognition should be combined with deep learning [6], [7], which can break through the limitations of communication protocol standards, such as frequency hopping, demodulation, interweaving,
encoding, encryption and other relevant techniques. However, deep learning could help to recognize ALE behaviors of a radio station by directly recognizing collected ALE signals. At present, the application of deep learning mainly focuses on signal classification and individual communication emitter recognition [8]–[11]. Sui et al. [12] propose a method for identification of communication emitter based on wavelet packet feature extraction and attribute reduction. In [13], Taylor polynomial model of communication emitter fingerprint is established, and FM algorithm is proposed to realize classification of signals. O’Shea et al. [14] conduct in-depth research on the performance of deep learning for radio signals classification, using methods of high-order moment and enhanced gradient tree for classification. And he also compare the performance of the two methods in range of configuration and channel loss. Zhou et al. [15] use bispectrum features of signals as the input of the de-noising auto-encoder and the depth confidence network to recognize the communication emitter. As an important network model in the field of deep learning, Convolutional Neural Network (CNN) can extract automatically deep features of signals [16]–[19]. LeNet [20], [21], GoogLeNet [22], [23], ResNet [24]–[26] and DenseNet [27], [28] are the classic representatives of a series of convolutional neural networks. In general, the more complex the network, the better the performance of the network in the field of computer vision.

Based on the analysis of link establishment behaviors of a short-wave radio station, it is obvious that different link establishment behaviors signals specified in the third-generation short-wave communication protocol standard (MIL-STD-188-141B) are very similar, and there are a little differences due to the original valid bits. Under actual battlefield conditions, such a little differences can hardly achieve the purpose of distinguishing different link establishment behaviors by traditional methods. However, a series of convolutional neural network can automatically extract the deep differences between signals. We would try to use some classic neural networks to recognize link establishment behaviors of a short-wave radio station, such as LeNet-5, ResNet-34 [29] and DenseNet-121 [30].

Actually, classic networks are mainly applied in the fields of images and videos. But the performance of these networks applied directly for unidimensional ALE signals is inconclusive. Seven kinds of ALE behaviors signals all belong to the same burst waveform, BW0. Hence, expert features of ALE behaviors are difficult to be extracted, such as amplitude features, frequency features, time-frequency features, bispectrum features, and other higher-order spectral features. So some traditional machine learning methods based on expert features are useless for ALE behavior recognition, such as Support Vector Machine (SVM) [31], [32], decision tree [33], K Nearest Neighbor (KNN) [34], [35] and K-means [36]. If the unidimensional ALE signals are directly processed by those machine learning methods, the ALE behaviors of a radio station would not be recognized correctly. In this work, DenseNet is adapted to be suitable for unidimensional signal input and deep features are extracted automatically by DenseNet without artificial help.

In this paper, we propose a novel approach for ALE behaviors recognition of a short-wave radio station without the radio station’s communication protocol, which uses DenseNet to automatically extract deep features of ALE signals. The performance of the DenseNet is enhanced by two parallel dense block in this work. The seven kinds of radio station’s ALE behaviors signals all belong to the same burst waveform, BW0, according to the communication protocol standard (MIL-STD-188-141B). Hence, the features of ALE behaviors are difficult to be extracted by human, so traditional machine learning methods are incapable. There is only one input in our improved unidimensional DenseNet and then the one input is put into two branches. The first branch use the original ALE behaviors signals, while the second branch use the processed ALE behaviors signals. The first half of BW0 burst waveforms are almost the same and the second half of BW0 burst waveforms carry different information. Therefore, the ALE behavior signal, whose first half is set to zero, is added to a parallel branch so that the performance of unidimensional DenseNet is better. Then we add the features extracted from the two parallel branches. Finally, we use the softmax classifier to recognize different ALE behaviors of a radio station. The results of comparison experiments also show that the improved unidimensional network in this work has better performance than other traditional networks.

The remainder of this paper is organized as follows. Section II introduces automatic link establishment behaviors signals of short-wave radio station. In Section III, the method of recognizing ALE behaviors and our improved unidimensional DenseNet are introduced in detail. And Section IV introduces the experimental results and analysis. Finally, Section V provides conclusions of the whole work.

II. AUTOMATIC LINK ESTABLISHMENT BEHAVIORS SIGNALS

According to the communication protocol standard (MIL-STD-188-141B), there are mainly five burst waveforms which correspond to different communication behaviors or states respectively in the process of radio stations’ communication. The automatic link establishment behaviors of a radio station all use the same burst waveform BW0 for communication. The number of valid bits in the BW0 waveform data frame is 26 bits, and the valid bits corresponding to different Link Establishment (LE) behaviors are slightly different, as shown in Fig.1.

As Fig.1 shows, different valid bits correspond to different communication behaviors during the process of link establishment, such as Call, Handshake, Notification, Time Offset, Group Time Broadcast, Broadcast and Scanning call. Different communication behaviors correspond to different function when establishing link between radio stations. Simple explanation of each LE behaviors is given, as shown in TABLE 1.
Recognizing ALE Behaviors of a Short-Wave Radio Station

FIGURE 1. Link establishment behaviors corresponding to different valid bits.

TABLE 1. Simple explanation of different LE behaviors.

| LE Behaviors          | Explanation                                                                 |
|-----------------------|-----------------------------------------------------------------------------|
| LE Call               | A radio station is willing to call other radio stations which could be a radio station or many radio stations in a group or in the same communication network |
| LE Handshake          | A radio want to continue to communicate with another radio station after it receive calling of other radio station |
| LE Notification       | A radio station want to give notification to all the other radio stations    |
| LE Time Offset        | Realize synchronizing time in the communication network                     |
| Group Time Broadcast  | Realize synchronizing time between radio stations in a communication group  |
| LE Broadcast          | A radio station sends commands to some other radio stations which need execute these commands |
| LE Scanning Call      | Two radio station start communication again meanwhile they already have each other’s information about the communication channel |

These valid bits shown in Fig.1 should be transmitted through BW0 burst waveform. The coding scheme and transmission scheme are shown in Fig.2.

As shown in Fig.2, the TLC/AGC guard sequence portion of the BW0 waveform provides an opportunity for both the transmitting radio’s Transmit Level Control process (TLC) and the receiving radio’s Automatic Gain Control process (AGC) to reach steady states before the BW0 preamble appears at their respective inputs, minimizing the distortion to which the preamble can be subjected by these processes. The TLC/AGC guard sequence is a sequence of 256 pseudo-random tribit symbols. The BW0 acquisition preamble provides an opportunity for the receiver to detect the presence of the waveform and to estimate various parameters for use in data demodulation. The preamble component of BW0 is the sequence of 384 tribit symbols. The TLC/AGC guard sequence and Acquisition preamble in all ALE behaviors signals are the same. The ALE signals differ due to valid bits highlighted in green, as shown in Fig.2.

According to communication protocol standard (MIL-STD-188-141B), the carrier frequency of signal is 1800Hz. In the process of simulation, the signal waveform is generated by the sharp-cosine filter. After signal is 4 times up-sampling, the sampling rate of ALE signal is 9600Hz and the code rate is 2400 symbols/second. Finally, the radio signals of the automatic link establishment behaviors is obtained, as shown in Fig.3.

Seven kinds of ALE behaviors of a radio station are simulated. In this work our goal is to recognize different ALE behaviors avoiding utilizing communication protocol of the radio station.

III. METHOD

A. ARCHITECTURE OF ORIGINAL DENSENET

DenseNet, which connects all layers (with matching feature-map sizes) directly with each other, ensures maximum information flow between layers in network. To preserve the feed-forward nature, each layer obtains additional inputs from all preceding layers and passes on its own feature-maps to all subsequent layers [30]. The architecture of an original dense block in DenseNet is shown in Fig.4.

If we use \( H_l(\cdot) \) to represent the nonlinear transformation function, including a series of operations, such as Convolution (Conv), Pooling, Batch Normalization (BN) Rectified Linear Units (ReLU) and so on. We denote the output of the \( l^{th} \) layer as \( y_l \), so the output of \( l^{th} \) layer in traditional neural network is

\[
y_l = H_l(y_{l-1}) (1)
\]

The output of the \( l^{th} \) layer in residual network is

\[
y_l = H_l(y_{l-1}) + y_{l-1} (2)
\]

And the output of \( l^{th} \) layer in DenseNet is

\[
y_l = H_l([y_0, y_1, \ldots, y_{l-1}]) (3)
\]

DenseNet is popularly used in two-dimensional image classification. We rarely find it applied directly to unidimensional radio signal classification. When network models have the same performance, DenseNet has fewer parameters than some classical convolutional networks, like VGG and ResNet. And not only can DenseNet take advantage of the deep features of ALE signals, but also it can take advantage of the shallow features of ALE signals. Comprehensive use of ALE signals’ deep features and shallow features can effectively prevent the network model from overfitting. Of course, the ability of DenseNet to automatically extract ALE signals’ features is the most important, which can avoid manually extracting features. Actually, features of different ALE behaviors signals might not be extracted easily by traditional means due to these signals are transferring by same burst wave called BW0 waveform shown in Fig.2.

B. UNIDIMENSIONAL DENSENET

For the purpose of recognizing different radio station behaviors, we should recognize unidimensional ALE signals directly instead of features extracted by human. The details of dense block in unidimensional DenseNet used in this work are shown as shown in Fig. 5.
next layer in Fig.5 is Fully Connected (FC) layer. In the end, we use the classifier to recognize ALE signals.

C. TOTAL NETWORK MODEL WITH IMPROVED UNIDIMENSIONAL DENSENET

Based on the characteristic of burst waveform BW0 in section II, an improved DenseNet is proposed. We use the network model with two parallel dense blocks to recognize radio station’s ALE behaviors, as shown in Fig.6.

The reason why we use two parallel dense block is that these second half of different ALE signals are different. Because these second half of signals are generated by valid bits which correspond to different ALE behaviors. In Fig.6, there is a zero setting operation at the top right-hand corner. By zero setting, we can not only retain the characteristics of different signals as much as possible, but also greatly reduce complexity of calculation. Different ALE signals all belong to the burst waveform, BW0. And BW0 has the same TLC/AGC guard sequence and Acquisition sequence, shown in Fig.2. So that the first half of ALE signal is set zero has very little impact on the performance of our network. However, we use the second half of ALE signal, which would improve the utilization efficiency of the signal features. There are mainly two reasons why only two different branches are used in the improved DenseNet. Firstly, too many branches will increase the complexity of the network, and the network may be difficult to converge. Secondly, the first half of the ALE signals are not exactly the same, we just think they are very similar. Therefore, when we use too many branches, it will reduce the impact of the first half of the ALE signals on the network performance. In that case, it is also not conducive to the application of our method in analyzing other radio station’s communication behaviors apart from ALE behaviors.

Our network model is expressed as:

\[
(y) = H((H_1(x) + H_2(x \ast c)))
\]

\[
c = \left[\begin{array}{c}
0 \\
\vdots \\
0
\end{array}\right] \ast 1 \ast 1
\]

where \(x\) denotes input signal, ‘\(\ast\)’ denotes two matrices are multiplied by their corresponding elements, \(H_1\) and \(H_2\) denote operation of two branches, \(H\) denotes the rest
FIGURE 6. Total network model with improved unidimensional DenseNet for recognition in this work.

operation in our network. $y$ denotes output of network, and $t$ denotes dimension of the input signal.

D. DETAILED PARAMETERS IN OUR NETWORK
The size of input signals is $(5888, 1)$, according to section II, where we simulate seven kinds of ALE signals. In fact, we simulate 14,000 signals for our experiments. The overall structure of improved unidimensional DenseNet used in our work is shown in TABLE 2.

As shown in Fig.6, there is a convolution layer after Dense Block. Because the output of the Dense Block concatenates all the layers within the block, the deeper the layer becomes with the more layers in the dense block, the greater the feature map size becomes. The existence of a convolution layer can reduce the feature map size.

Our network has only one input. Then the input passes through two branches. Deeper features of signal are extracted by two Dense Blocks. Afterwards, we sum the feature maps of two branches’ output. In the end, we recognize ALE signal by Classification Layer.

IV. EXPERIMENTAL RESULTS AND ANALYSIS
In this section, the performance of the proposed improved unidimensional DenseNet is analyzed by using simulation data. We add Gaussian white noise to simulated ALE signals and therefore we simulate the ALE signals passing through communication channels with different quality. We use SNR to represent different quality of communication channels. The scenario we hypothesize is how to recognize a radio station’s ALE behaviors after intercepting the radio station’s electromagnetic signal. The ALE behaviors signals are simulated according to the communication protocol, but the communication protocol is not utilized during in the process of ALE behaviors recognition. So our experiment is logic and reliable.

There are seven kinds of ALE signals of radio station, including Call, Handshake, Notification, Time Offset, Group Time Broadcast, Broadcast and Scanning Call. The ALE signal length is $t = 5888$. For each kind of ALE signal, we simulate 2000 samples. There is a total of 14000 samples used in experiments.

Experimental environment: NVIDIA GEFORCE GTX 950M, Keras 2.2.5, and Tensorflow 1.12.0.

A. THE PERFORMANCE OF IMPROVED UNIDIMENSIONAL DENSENET
We randomly select 1400 samples, 2800 samples, 4200 samples, 5600 samples, 7000 samples, 8400 samples, 9800 samples, 11200 samples, and 12600 samples from all the 14000 samples for training and respectively the rest for testing. We set epoch of network is equal to 15 and batch size is equal to 8. Finally, we obtain the recognition accuracy of improved DenseNet when SNR $= -5$ dB, 0 dB, and 5 dB, as shown in Fig.7.

As shown in Fig.7, if SNR is equal to 5 dB, the recognition accuracy of improved unidimensional DenseNet is very high even while the number of training samples is small. However, if SNR is equal to 0 dB, the recognition accuracy of improved unidimensional DenseNet is not greater than 90% while the number of training samples is smaller than 2800. Particularly, when SNR is equal to $-5$ dB, the recognition accuracy is about 70%.

According to the experiment, it shows that the more samples we use for training, the better performance of improved unidimensional DenseNet we have. And when SNR is greater than 0 dB, the improved unidimensional DenseNet can effectively recognize ALE behaviors of short-wave radio station. It also shows that we can recognize radio station’s ALE behaviors by directly analyzing the radio signal, without knowing radio station’s communication protocol.

B. COMPARISON EXPERIMENTS
There two branches in improved unidimensional DenseNet, as shown in Fig.6. The right branch is added to enhance the performance of network. In the following experiment, we compare the performance of simple unidimensional DenseNet (there is only a branch in the network) with the performance of improved unidimensional DenseNet. We randomly select 8400 samples as the training set and the remaining 5600 samples as the test set. Batch size is 8 when we are training network. The experimental results are shown in Fig.8 when SNR $= -5$ dB, 0 dB, 5 dB.
TABLE 2. Improved unidimensional densenet architecture used for our research. Each “Conv” layer consists of the sequence of batch normalization (BN), rectified linear unit (ReLU), and convolution layer. “s1” and “s2” represent strides of 1 and 2 pixels, respectively.

| Layer               | Input Size | Output Size |
|---------------------|------------|-------------|
| ALE Signal Input Layer | 5888×1     | 5888×1      |
| Two Branches Layer  | 5888×1     | 5888×1      |

| Dense Block | 3(kernel size) Conv, s1 | The size of convolutional kernel is 3 |
|-------------|-------------------------|-------------------------------------|
|             | 5888×1                  | 5888×1                             |
|             | 5888×128                | 5888×128                           |

| Maxpooling Layer | The size of pooling is 2 |
|                 | 5888×32                 | 5888×32                           |
|                 | 2944×32                 | 2944×32                           |

| Sum Layer       | 2944×32                 | 2944×32                           |
| Flatten Layer   | 2944×32                 | 94208                             |
| Classification Layer | Fully-connected | 94208                             |
|                 | 256                     | 7                                 |

As Fig.8 shows, the training loss of improved unidimensional DenseNet decreases faster than the training loss of simple unidimensional DenseNet, especially when epoch is smaller than 3. It means the speed of training improved unidimensional DenseNet is higher than the speed of training simple DenseNet. By comparing Fig.8(a), Fig.8(b) and Fig.8(c), it is obvious that training loss declines faster as SNR increases, which is consistent with the practical situation. When epoch is equal to 15, recognition accuracy of simple DenseNet and improved DenseNet on test set is shown in TABLE 3.

As shown in TABLE 3, the recognition accuracy of improved unidimensional DenseNet is higher than simple unidimensional DenseNet. When SNR is −5dB, 0dB, and 5dB, the accuracy of improved DenseNet increase by 1.97%, 1.19%, and 0.76%, respectively compared with simple DenseNet. So it could improve the performance of network if we add another dense block to simple unidimensional DenseNet. The effective features of ALE signals are emphasized by these two dense block and features of ALE signals are reused by dense block, so improved unidimensional DenseNet in this work have better performance for recognizing ALE behaviors of radio station. Meanwhile, the simple unidimensional DenseNet spend about 41ms averagely training each sample, while the improved DenseNet spend about 53ms averagely training each sample. Actually, there are 24,171,563 parameters and 24,152,227 parameters in improved DenseNet and simple DenseNet, separately.

FIGURE 7. The performance of improved DenseNet with different number of training samples.
Overall, compared with the simple network, the improved DenseNet is not much more complicated. And the training time cost increase very little.

In addition, the improved unidimensional DenseNet has high accuracy when SNR is greater than 0dB. Meanwhile, the high accuracy shows that we can effectively recognize ALE behaviors of a radio station without using its communication protocol. It is a novel inspiration for the field of electronic countermeasures.

In section II, we have stated that seven kinds of ALE behaviors signals belong to BW0 burst waveform, and thus the features of these ALE signals are almost the same in frequency domain, time-frequency domain and other transformation domain. So some methods of traditional machine learning will no longer work due that they rely on artificially extracted features, such as SVM, Random Forest [37], [38], and KNN. In particular, the simulated ALE signal has 5,888 points, and it is impractical to directly recognize it by using methods of traditional machine learning. We use convolution neural network to automatically extract features of ALE signals avoiding the process of artificially extracting features.

Actually there are two ways to directly recognize ALE signals of radio station. The first way is to reshape a unidimensional ALE signal into a two-dimensional matrix and then use convolutional neural network applied for images classification to recognize ALE signals. The second way is to make neural network applied for image classification change to be suitable for unidimensional ALE signals recognition. Some classical neural networks will be used to recognize ALE signals of a radio station in these two ways in this work.

When we train networks until epoch is equal to 15. The experimental results using the first way are shown in TABLE 4. These classic networks we use include DenseNet-121, ResNet-34, and LeNet-5. We randomly select 8400 samples as the training set and the remaining 5600 samples as the test set. Batch size is 8 when we are training network.

As shown in TABLE 4, when SNR is 5dB, only LetNet-5 can recognize ALE behaviors of a radio station and its accuracy is 99.14%, while other networks are incapable.

**TABLE 3. Recognition accuracy of simple densenet and improved densenet.**

| Network Model      | SNR(dB) | Recognition Accuracy(%) |
|--------------------|---------|-------------------------|
| Simple DenseNet    | -5      | 68.82                   |
| Improved DenseNet  | -5      | 70.79                   |
| Simple DenseNet    | 0       | 97.00                   |
| Improved DenseNet  | 0       | 98.19                   |
| Simple DenseNet    | 5       | 99.17                   |
| Improved DenseNet  | 5       | 99.93                   |

**TABLE 4. Recognition accuracy of classic neural networks using the first way.**

| Network Model | SNR(dB) | Recognition Accuracy(%) |
|---------------|---------|-------------------------|
| DenseNet-121  | 0       | 13.96                   |
| ResNet-34     | 0       | 14.34                   |
| LeNet-5       | 0       | 13.54                   |
|               | 5       | 99.14                   |
When SNR is 0dB, all the networks above are incapable. Thus, the way that we firstly reshape unidimensional ALE signal into two-dimensional matrix and then use network to recognize ALE behaviors is not better than our improved unidimensional DenseNet.

The second way is that we make DenseNet be suitable for unidimensional input and then achieve recognizing ALE behaviors of a radio station. When we train networks until epoch is equal to 15. The experimental results using the second way are shown in Table 5. These classic networks we use include DenseNet-121, ResNet-34, LeNet-5 and Multilayer Perceptron (MLP) [39], [40]. There are two hidden layers in the MLP. And the number of neurons are 1000 and 256 in the two layers, respectively. In addition, we add operation of batch normalization in the two hidden layers. At last, we randomly select 8400 samples as the training set and the remaining 5600 samples as the test set. Batch size is 8 when we are training network.

As shown in Table 5, MLP and improved DenseNet in this work are able to recognize ALE behaviors of a radio station. When SNR is -5, 0, 5, the accuracy of improved DenseNet is 70.79%, 98.19% and 99.93%, respectively, and the accuracy of MLP is 64.04%, 86.65% and 97.56%, respectively. Compared with the recognition accuracy of MLP, the recognition accuracy of improved DenseNet increase by 6.75%, 11.54% and 2.37%, respectively. Meanwhile, our method could be optimized because different filters and structures of network model also has better performance than other classic methods.

In future of work, we hope to do more researches to perfect the improved unidimensional DenseNet. Firstly, there are many samples with labels used for training network, which is uncommon in the real electronic reconnaissance. Secondly, the ALE signals should be collected in real electronic environment and then recognized by improved DenseNet. The ALE signals strength will affect the performance of our network. So in the real communication environment, we need to consider whether we can receive ALE signals and how to effectively improve the quality of ALE signals. Thirdly, the improved DenseNet could continue to be optimized because different filters and structures of network can improve the performance. Lastly, our method could be purposely applied to analyze communication behaviors of other radio stations using different communication protocol standard.

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As shown in Table 5, MLP and improved DenseNet in this work are able to recognize ALE behaviors of a radio station. When SNR is -5, 0, 5, the accuracy of improved DenseNet is 70.79%, 98.19% and 99.93%, respectively, and the accuracy of MLP is 64.04%, 86.65% and 97.56%, respectively. Compared with the recognition accuracy of MLP, the recognition accuracy of improved DenseNet increase by 6.75%, 11.54% and 2.37%, respectively. However, other classic networks adapted for unidimensional signals are unless for recognizing ALE behaviors. The experimental results also show that very complex networks are not suitable for the field of unidimensional signal recognition.

According to Table 4 and Table 5, our improved unidimensional DenseNet has the best performance compared with other networks. And we can recognize ALE behaviors of a radio station by using improved DenseNet, even though we do not know the communication protocol of the short-wave radio station.

### Table 5. Recognition accuracy of unidimensional networks and improved unidimensional DenseNet using the second way.

| Network Model               | SNR(dB) | Recognition Accuracy(%) |
|-----------------------------|---------|-------------------------|
| Unidimensional DenseNet-121 | 0       | 14.17                   |
|                            | 5       | 14.34                   |
| Unidimensional ResNet-34    | 0       | 14.25                   |
|                            | 5       | 14.25                   |
| Unidimensional LeNet-5      | 0       | 13.54                   |
|                            | 5       | 99.78                   |
| MLP                         | -5      | 64.04                   |
|                            | 0       | 86.65                   |
|                            | 5       | 97.56                   |
| Improved Unidimensional DenseNet | -5   | 70.79                   |
|                             | 0       | 98.19                   |
|                             | 5       | 99.93                   |

V. CONCLUSION

Considering the difficulty to recognize ALE behaviors of a short-wave radio station without knowing the communication protocol of the radio station. The signals of different ALE behaviors are analyzed and simulated. And this paper proposes a method to recognize ALE behaviors by analyzing unidimensional ALE signals directly, even though communication protocol is not acquired. Firstly, based on the advantages of DenseNet in automatically extracting deep features of ALE signals, original DenseNet is adapted for unidimensional ALE signals, and then two parallel dense blocks are adopted to enhance the performance of networks. Finally, the ALE behaviors recognition of a radio station is realized by improved unidimensional DenseNet. The experimental results show that the proposed method is feasible and effective. When SNR is -5dB, 0dB, and 5dB, compared with the recognition accuracy of simple unidimensional DenseNet, the recognition accuracy of improved DenseNet increase by 6.75%, 11.54% and 2.37%, respectively. Meanwhile, our network model also has better performance than other classic methods.

In future of work, we hope to do more researches to perfect the improved unidimensional DenseNet. Firstly, there are many samples with labels used for training network, which is uncommon in the real electronic reconnaissance. Secondly, the ALE signals should be collected in real electronic environment and then recognized by improved DenseNet. The ALE signals strength will affect the performance of our network. So in the real communication environment, we need to consider whether we can receive ALE signals and how to effectively improve the quality of ALE signals. Thirdly, the improved DenseNet could continue to be optimized because different filters and structures of network can improve the performance. Lastly, our method could be purposely applied to analyze communication behaviors of other radio stations using different communication protocol standard.

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