Toward Convolutional Neural Networks on Pulse Repetition Interval Modulation Recognition

Xueqiong Li, Zhitao Huang, Fenghua Wang, Xiang Wang, and Tianrui Liu

***Abstract*— In modern electronic warfare environments, there are multiple-radar transmitting signals. For an electronic support system, it is essential to recognize the modulation of pulse repetition intervals (PRIs), since it is directly related to the indication of radar emitters. However, PRI modulations are more difficult to recognize in modern electronical environments due to the high ratio of lost and spurious pulses. Therefore, a fully automatic approach for recognizing seven PRI modulation types using a convolutional neural network (CNN) is proposed in this letter. Simulation results show that our CNN-based recognition method not only promotes performance but is also robust to the environment with lost and spurious pulses. The recognition accuracy is 96.1% with 50% lost pulses and 20% spurious pulses in simulation scenario.**

***Index Terms*— Convolution neural network, pulse repetition interval, modulation mode, recognition, electronic support system.**

I. Introduction

SIGANLS EMITTED by multiple radars are intercepted by an Electronic Support (ES) system, thereafter and de-interleaved into individual pulse trains. Then the ES system identifies each radar signal by comparing them with the data stored in the database [1]. Pulse Repetition Interval (PRI) is one of the most significant feature to describe the pulse trains since it describes the pattern of intervals between the leading edges of successive radar pulses. Knowledge of PRI modulation mode can significant facilitate the indication of radar emitter in the process of radar emitter recognition. However, with the steady advancement of countermeasures and the increasing number of independent emitters, the signal environment of electronic warfare is becoming denser and PRI modulations are becoming more complicated. Therefore, conventional methods can hardly recognize the PRI modulation accurately. A new approach with higher accuracy and efficiency is required.

Several intelligent techniques have been proposed in order to realize PRI modulation recognition. In [2], the SVM classifier can achieve lower error rate of recognition and is also more robust to noise. A robust method combining previous methods with simpler classifiers to speed up recognition process was presented in [3]. A method using symbolization to recognize PRI modulation type was introduced in [4]. In [5], a technique compares the characteristic quantity with a threshold value to recognize PRI modulation modes. Those intelligent techniques mentioned above have recognized some of the basic PRI modulation modes, but at a cost of a large amount of work on data pre-processing. Meanwhile, the results cannot adjust to the environment with a high ratio of lost pulses and spurious pulses. The recognition method based on the autocorrelation feature is proposed in [6]. The autocorrelation feature is robust to noise pulses, but it is vulnerable to pulse missing. The newest research on PRI modulation recognition is described in [7] and achieve over 99% accuracy. A neural network is used to categorize four kinds of PRI modulation, but only under a low ratio of errors and data pre-processing has to be done before the recognition.

In this letter, we propose an approach using CNN to recognize seven PRI modulation modes. The novelty of this technique is to take advantage of CNN's characteristics of invariance to small shifts through the use of local filtering and max-pooling. In this way, practical PRI sequences with noises can be well recognized. Meanwhile, the PRI sequences, in our method, can be directly input in to the CNN, with no need of extra preprocessing steps for unique feature extraction. The experimental results have indicated that the CNN based method proposed in this article can recognize seven kinds of PRI modulation modes with 96.1% recognition accuracy under utmost 50% lost pulses and 20% spurious pulses in simulation scenario.

II. PRI Modulation Modes

In general, PRI modulation can be classified into seven basic modes, i.e., fixed PRI, jittered PRI, staggered PRI, sliding PRI, agile PRI, D&S (Dwell and Switch) PRI and wobulated PRI. These seven PRI modulation modes have different characteristic described as follows.

Fixed PRI. Fixed PRI sequence has a stable value that will never change under ideal circumstances.

Jittered PRI. The value of jittered PRI sequence jitters around a certain PRI value, and the range of jitter is always between 1% and 30% of PRI value and the jittered value which is random but typically Gaussian or uniform.

Staggered PRI. Several (2 to 7 typically) stable PRI values appear in cyclic order for staggered PRI sequences.

Sliding PRI. Sliding PRI is the sequence whose PRI values monotonously increase (or decrease) to an extreme value. When it reaches the maximum (or minimum) value, it sud-

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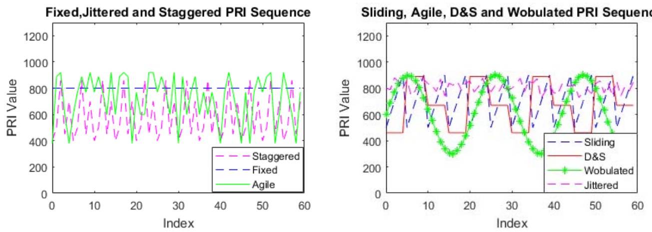


Fig. 1. Different kinds of PRI modulation modes.

denly goes down (or up) to the minimum (or maximum) value.

Agile PRI. Agile PRI has several certain PRI values like staggered PRI, but the difference is that these values are not changing in order, but in a random sequence.

D&S PRI. Some constant values of PRI are used in dwell and switch PRI sequences. However, the difference between D&S PRI and staggered PRI is that the PRI remains on one certain value for a short duration, and then switches to another value in D&S PRI sequences.

Wobulated PRI. Wobulated PRI sequence has the similar shape as a sinusoidal function, and it comes up periodically.

The values of seven kinds of PRI range from 200 to 2,000, which are set according to real EW environment. The detailed simulation parameters are described in Section IV. The curve of PRI sequences of seven modulation modes in ideal environment are shown in Figure 1.

In practical, PRI sequences can have high ratio of lost and spurious pulses due to the influence of noise. Let $\{p_n\}$ represents for a pulse train, the new PRI sequence $\{p'_n\}$ is generated with lost pulses from the ith to the $(i+j)$th pulses, i.e.

$$p'_n = \begin{cases} p_n & n = 1, 2, ..., i-1 \\ p_i + \ldots + p_{i+j+1} & n = i \\ p_{n+j+1} & n = i+1, ..., N-j-1. \end{cases} \tag{1}$$

where N is the number of pulses.

As for spurious pulses, if j pulses are attached to the ith pulse, the new PRI sequence p''_n has been created as

$$p''_n = \begin{cases} p_n & n = 1, 2, ..., i \\ p_i + \ldots + p_{i+j+1} & n = i+1, ..., i+j \\ p_{n-j} - T_i & n = i+j+1 \\ p_{n-j} & n = i+j+2, ..., N+j, \end{cases} \tag{2}$$

where T_i is the interval between the last spurious pulse of the ith pulse and the next real pulse.

III. CNN Based Modulation Recognition Method

Convolutional Neural Networks (CNNs) have been widely utilized in the digital image recognition area and achieved huge success. CNN can leave out complex data pre-processing and extract the features automatically. Meanwhile, it can adapt to environment with missing and false information. These characteristics of CNN have exactly satisfied the need of PRI modulation mode recognition.

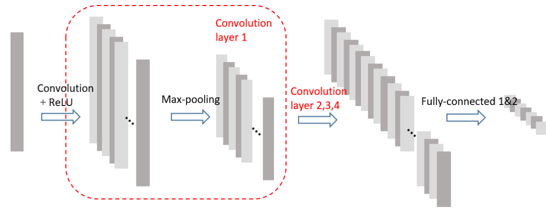


Fig. 2. CNN structure of the proposed PRI modulation recognition method.

A. Proposed CNN Structure for Modulation Recognition

We propose CNN structure according to the complexity of our data. The network, as shown in Figure 2, composites of 4 convolution layers, 2 max-pooling layers, and 2 fully connected layers. The vectors which output from the network are fed into a softmax function for classification. The main components of our proposed network are described as follow.

B. Input and Output

Let $\boldsymbol{x} \in \mathbb{R}^{h\times\omega\times c}$ be the input data of simulated PRI sequences, where h, ω, c represents for the height, width and number of channels. Unlike images which are two-dimensional data, PRIs have only one dimension. Therefore, the parameter h equals to 1 throughout the whole process. In our structure, ω is a constant which means our data have the same length. The dimension of the input channel is 1. A block takes $\boldsymbol{x}$ and a set of parameters W as input and produces a vector $\boldsymbol{y} \in \mathbb{R}^{h'\times\omega'\times c'}$ as output, where x is the input and W is the weight matrix, i.e. $\boldsymbol{y} = f(\boldsymbol{x}, W)$.

C. Main Layers

There are mainly three kinds of layers in our CNN structure including four convolutional layers, two pooling layers and two fully connected layers. The first convolution layer C_1 has 32 filters with kernel size 3. The second convolution layer C_2 has 64 filters with kernel size 3. The third and fourth convolution layers C_3 and C_4 are of the same structure with 128 filters and kernel size 2. The computation of convolutional layers can be formulated as

$$\boldsymbol{y} = f(\boldsymbol{b}_{k'} + \sum_{i=1}^{h}\sum_{j=1}^{\omega}\sum_{d=1}^{c} W_{ijdk'} \times \boldsymbol{x}_{i'+i,j'+j,d}), \tag{3}$$

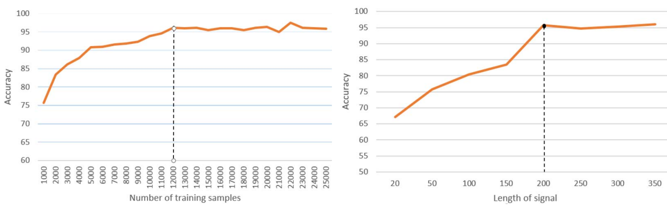
where the input $\boldsymbol{x}$ with a number of filters $W \in R^{h'\times\omega'\times c'}$, also called as kernels, and adds a bias $\boldsymbol{b} \in R^{c'}$. $f(\centerdot)$ denotes a nonlinear function.

Max-pooling layers are used after convolution in order to perform down-sampling and the size of feature maps through a max-pooling layer will be reduced by $1/2$. There are two max-pooling layers which followed the first two convolutional layers in our CNN structure.

Finally, 2 fully connected layers followed all the convolution and pooling layers. In this way, every kernel in these layers are connected to all the feature maps in the previous layers. The first fully connected layer has 64 neurons while the other has 7 neurons in order to do classification.

TABLE I
PARAMETER SETTINGS OF DIFFERENT ENVIRONMENT

Scene	measuring error (%)	lost pulses (%)	spurious pulses (%)
ideal	0	0	0
extreme	5	80	50
typical	1	50	20



(a) (b)

Fig. 3. Accuracy under different amount and length of samples.

IV. SIMULATION RESULTS

A. Errors in Reality

In order to simulate the real situation of modern ES environment, three variations are taken into consideration, i.e., measuring error, rate of lost pulses and spurious pulses.

We perform simulation under three different parameter settings for the environment, namely, ideal environment, extreme environment and typical environment. The measuring error follows a Gaussian noise function, where the Gaussian mean values are the values of PRI and the Gaussian variances are the measuring errors. Other two noises are simulated as in equation (1) and (2) in Section II. The ideal environment and extreme environment represent the best and worst situation of the real environment respectively, and both of them do not have high possibility to occur. Meanwhile, the typical environment always happens in real ES environment. The parameters of different environment are showed in Table 1.

B. Parameter Settings

There are several parameters to be set for the CNN structure and for the dataset. Those parameters are set through cross-validation to make the recognition achieve the best performance. Some of the parameters are set through a large amount of experiments, the process can be found in the following sub-sections. In training phase, we initialize the weights using random initialization ranging from 0 to 1. In all the experiments, we use 90 percent of data for training and 10 percent of data for validation. Besides, forwarding a batch of data consisting of 100 data points takes less than 0.3 ms on a computer with 1.6 GHz Intel Core i5 processor and 8 GB 1600 MHz DDR3 memory.

1) The Amount and Length of Dataset: There are two parameters of dataset including the number of the training samples and the length of the signal. There are a lot of experiments undertaken to obtain the best amount and length of dataset to get the best performance. Figure 3 (a) is the accuracy curve under different amount of training samples where the horizontal axis represents for the sample number of a single modulation mode. Figure 3 (b) shows the accuracy with different length of samples.

It can be seen from Figure 3 that when the amount of training samples reach about $12,000$ for each modulation mode, the accuracy gradually converges. Meanwhile. when the length of PRI sequence reach around 200, the curve stay at the same level. Considering of the computation quantities, we set the amount of samples and length of samples at $12,000$ and 200 respectively.

2) Number of Convolutional Layers: Setting the number of convolutional layers is the most significant part of the whole process since the number of times of convolution decide whether the correct features can be obtained and the results are perfect. Firstly, a simple 2 layers of convolution structure is being tested. Then, we gradually added convolution layers to see how the performance go under these different structure. The results show that accuracy can reach about 74.6 with 2 convolutional layers and then it increases to 96.1% of with four convolutional layers. After that, 5 layers or more of convolutional layers results in lower accuracy with certain input. Vanishing gradient problem is the main problem causing the degrading of accuracy, a further study on dealing with vanishing gradient problem can be implemented to improve the performance.

3) Other Parameters: Other parameters including the number of max-pooling layers and fully connected layers, number of neurons of each layer, rate of dropout of each layer, etc. The performance could be better with higher accuracy if we give more dataset and larger CNN structure, but the performance gain is minor. Considering of the computation quantities and time consumption, the parameters with highest performance-price ratio are set to pursue high performance with relative low cost.

C. Results

Firstly, the CNN structure mentioned before is directly used to recognize seven PRI modulation modes. It turns out the recognition accuracy of agile PRI is evidently lower than other kinds as can be seen in Figure 3. This is because agile PRI is easy to be recognized as D&S PRI sequence with high lost pulses and spurious pulses.

In order to specify agile PRI and D&S PRI, a small improvement is made to the process. Agile PRI and D&S PRI are seem as one mode at first. After being categorized via CNN structure, a further recognition is take. The only thing should be focus on for this step is to see whether the values of PRI sequence is changing greatly every time. If it is changing all the time obviously, then it is agile PRI and vice versa. The whole process is described as Figure 4.

Using this process, the whole categories are being tested in three simulation environments. Three methods are compared, i.e., the traditional method, common neural network method (FC) and CNN method. Traditional method always compare the different changing regulation among the PRI sequences. Common neural networks method uses fully connected networks to recognize PRI modulation modes. The results are showed in Table 2.

As can be seen from the results, traditional method and common neural network can recognized those modes in ideal environment well. However, with the increasing of errors,

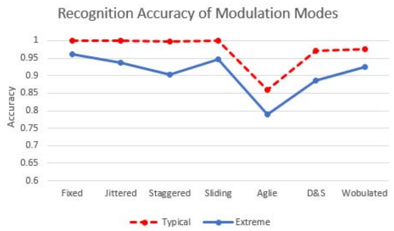


Fig. 4. Result of each modulation mode with CNN structure.

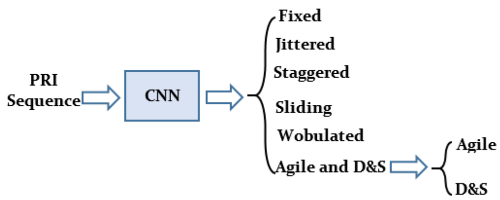


Fig. 5. The whole process of PRI modulation recognition.

TABLE II

RECOGNITION RESULTS UNDER DIFFERENT CIRCUMSTANCES

No.	Scene	method	accuracy
1	ideal	traditional	99%
2	ideal	FC	89.8%
3	ideal	CNN	99.4%
4	typical	traditional	57%
5	typical	FC	62.8%
6	typical	CNN	96.1%
7	extreme	traditional	/
8	extreme	FC	46.8%
9	extreme	CNN	84.9%

only the proposed CNN based method can still recognize those modes with high accuracy. Even in extreme environment, CNN can reach 84.9% of recognition accuracy.

As the amount of constant term is too large, Floating Point Operations Per Second (FLOPS) is often used to measure the time complexity in neural network. The FLOPS of the whole neural network is $O\left(\sum_{l=1}^{D} M_l^2 K_l^2 C_{l-1} C_l\right)$, where D is the depth of CNN, M and K represent the length of feature map and kernel of lth layer, C is the number of channel. In our CNN structure, the time complexity is 4.2Gflpos.

D. Analysis and Discussion

As CNN method has significantly improved the performance of PRI modulation recognition with lost pulses and spurious pulses, the structure of CNN has been analyzed. There are two features of CNN that make CNN really suitable for solving PRI modulation mode recognition problem.

1) Locality: PRI sequences have locality characteristic along with time axis, which means different modulation modes do not have the same period features along the time axis. These period features represent the characteristics of each kind of modulation, and become the critical clues to distinguish different modulation modes.

When dealing with high-dimensional inputs, CNN only connects every neuron to a local region of the input volume. The connections are local in space. CNN is able to model these features with local period by allowing every node of convolutional layers to receive input data from features which can represent a special characteristic of the whole PRI sequence only. For example, when recognizing a chair in an image, CNN can find it out no matter the location of the chair in the image. This specialty of CNN fits PRI sequences quite well. CNN can find out the local period features of PRI sequences so that recognize which modulation modes this PRI sequence belongs to.

2) Tolerance of Shape Changes and Displacement: As discussed above, PRI sequences have many local period features and these features are distributed on the time axis, where every feature will appear to the center around a particular time which varies in a limited range. That is to say, there are a lot of shape changes and displacements due to errors caused by transmitting and intercepting signals.

In order to deal with the problem of variability in CNN, max-pooling layers are inserted into the network structure. Generally, the activations of max-pooling layers are divided into some bands and the input of every band is the output of previous convolution layer representing the maximum activations received from the convolution filters within these bands. Finally, there are a smaller number of bands can be obtained which provide a lower resolution feature which contain more useful information that will be further processed by higher layers in the network structure.

V. CONCLUSIONS

In this letter, we proposed a CNN based method for PRI modulation modes recognition. The result shows that using convolution and max-pooling significantly improves the recognition performance. Simulation results show the overall ratio of recognition is 96.1% with utmost 50% lost pulses and 20% spurious pulses. Besides, our methods need no data preprocessing, since features can be automatically extracted by the neural networks. This will help ES systems to analyze pulses in real time. Future works may include experiments on real data. Network of deeper structure is also a direction.

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