Radar Emitter Identification Based on Fully Connected Spiking Neural Network

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Abstract. In the face of the increasing complex electromagnetic environment and new radar system, it is difficult to extract radar emitter characteristics based on manual mode to meet requirements of modern cognitive electronic warfare. In order to improve the intelligence level of radar emitter identification, a new method based on Spiking Neuron Network (SNN) for radar emitter identification is proposed in this paper. Firstly, five kinds of common radar signals are converted into two-dimensional gray scale images by using time-frequency analysis method. Then, the images are converted into spikes by Poisson coder, which are put into a fully connected spiking neural network for training and emitter identification. Finally, the simulation results prove the validity of this method by comparing with the traditional neural network.

Keywords: Spiking Neuron Network, Radar Emitter Identification, Deep Learning

1. Introduction
Radar emitter identification is an important way for intelligence reconnaissance and enemy information obtaining. Accurate radar emitter identification is the key to grasp the initiative of war. Traditional radar emitter is identified by extracting the feature vector of pulse description word, such as template matching, expert system and so on. With the increasing complexity of modern radar signal characteristics, traditional radar emitter identification technology cannot adapt to the field of modern radar emitter identification.

Recently, more and more attention has been paid to the radar emitter recognition based on deep learning, due to its powerful feature extraction ability and good generalization ability. In reference [1], a Stacked Auto-Encoder is proposed to identify radiation sources. Reference [2] and [3] propose Convolutional Neural network (CNN) and Improved CNN to identify radar emitter. In reference [4], Visual Geometry Group (VGG) is proposed for radar emitter identification. However, most of these neural networks have the disadvantages of long time training, large computation and high power consumption. In this paper, spiking neural network is used to identify radar emitter in this paper. Compared with these traditional neural networks, this method has higher recognition rate and works well in low SNR.

2. Basic principle of spiking neural network
Spiking neural network is known as the third generation artificial intelligence network. Neuron is an important part of neural network for transmission information between neurons to simulate brain work. At present, most of neuron models are “M-P Neuron Model”[6], the input and output of neuron are a specific value. Unlike traditional neural networks, the input and output of a spiking neural network are
a series of spikes with a specific fire rate instead of a specific value. SNN uses the precise timing of spikes to provide powerful computing power like a true brain. The power consumption of a spiking neural network running on a proprietary neuromorphic hardware (such as TrueNorth) is only a few thousandths of consumption of a conventional neural network for the same task[7].

2.1. Neuron model
Classical neuronal dynamics models include Hodgkin-Huxley model[8] and leaky integrate-and-fire(LIF) model[9] . The Hodgkin-Huxley model is accurate but with high computational complexity. The LIF model can greatly reduce the amount of computation on the basis of simulating the behaviour of real neurons. The LIF model is an perfect model for the study of both individual neurons and neural networks: simple enough but accurate enough to describe the changes in membrane voltage, leakage current, and refractory periods of neurons[10], which makes the LIF model often used in various experiments. Figure 1 shows the relationship between voltage change (left) and spikes (right) of LIF model in thermodynamic diagram form. The number of neurons is 16 and simulation step size is 100.

![Figure 1](image1.jpg)

**Figure 1.** Voltage change (left) and the spikes (right) of LIF model in thermodynamic diagram form

2.2. Image classification by SNN
Firstly, the image is converted to a series of spikes which fit Poisson process by Poisson encoder. Then the spikes are sent to a SNN[11]. In this paper, the input is voltage increment caused by spikes, while the hidden state is membrane voltage and output is the spikes.

For example, a Lena grayscale image runs 512 steps in simulation with 1,128,256,512 overlay steps to get the results as shown in figure 2:

![Figure 2](image2.jpg)

**Figure 2.** Lena gray scale image runs 512 steps in simulation with 1,128,256,512 overlay steps.

It is known that SNN can restore images when the number of simulation steps is large enough. Using supervised learning and error back propagation, SNN has the ability of image classification by adjusting the weights of the synapses between neurons. After the time-frequency conversion of the radar emitter signal into a two-dimensional image, it is feasible for SNN to identify the emitter using this characteristic. Through time-frequency conversion, radar emitter signal can be converted into an image. It is feasible for SNN to identify the emitter using this characteristic.
3. Feature extraction of radar emitter

In traditional radar data processing, only a single feature in time domain or frequency domain is used, and the time-frequency feature map can represent signal in both time domain and frequency domain\[12\]. Time-frequency transformation is obtained by integrating two-dimensional joint function of time-frequency\[13\], and different time-frequency distributions can be obtained by selecting different kernel functions\[14\]. In this paper, the Bord-Jondan distribution is used to realize time-frequency two-dimensional image of radar emitter. The expression is as follows:

\[
C_x(t, f) = \int \int \phi(t-t', \tau) x(t' - \frac{\tau}{2}) x(t' + \frac{\tau}{2}) e^{-j2\pi f t'} dt' d\tau
\]

(1)

\[
\phi(t, \tau) = \begin{cases} 
1 & \left| \frac{t}{\tau} \right| < \frac{1}{2} \\
0 & \left| \frac{t}{\tau} \right| > \frac{1}{2}
\end{cases}
\]

(2)

Where \(\phi(t, \tau)\) is the kernel function. In this paper, five kinds of common radar modulation modes are used: Frequency Shift keying (FSK), Binary Phase Shift Keying (BPSK), Continuous Wave (CW), Linear Frequency Modulation (LFM) and Nonlinear Frequency Modulation (NLFM). The Bord-Jondan time-frequency distribution image of radar emitter when SNR is 0 dB is shown in figure 3:

![Figure 3. Five common kinds of radar modulation modes.](image)

4. Construct SNN

In order to improve the accuracy, this paper uses three-layer full-connection SNN, and each layer is made up of LIF neurons. The SNN parameters are as follows: Adam optimizer, Poisson encoder, MSE loss function, the size of input layer is 64*64, the size of hidden layers is 32*32 and 14*14 respectively, the number of output neurons is 5. Taking the FSK as an example, the network structure is shown in figure 4:

![Figure 4. The structure of spiking neural network.](image)
FSK time-frequency two-dimensional image is the first category. Only correctly classified neuron (the first) has the highest firing rate, and the other neurons remain silent.

5. Experimental results and analysis
Each category of training set produces 10,000 images and 50,000 images in total. The test set generated 2,000 images for each category, where 10,000 images in total. Training parameters: batch-size is 64, learning rate is 0.001, epoch is 20. LIF Neuron parameters are as follow: step length is 100, time constant is 100 ms, threshold voltage is 1 V, and reset voltage is 0 V. The experimental software environment is based on open source deep learning framework pytorch 1.6 model using CUDA10.1 to provide support for GPU operations and improve the speed of parallel graphics operations. Hardware environment: Titan Xp(GPU), Intel i7-7700K@4.20GHz(CPU).

![Graph](image_url)

**Figure 5.** The test accuracy under different SNR conditions after training 20 epochs.

As can be seen from the Figure 5, when SNR is 0 dB or -5 dB, the precision of this method can reach 100%. When SNR is -10dB, the test precision still keep as high as 95.4%.

Under the same condition, the average identify rate compared with other references after 100 epochs of training is shown in table 1:

| SNR/dB | Ref[1] | Ref[2] | Ref[3] | Ref[4] | Method in this paper |
|--------|--------|--------|--------|--------|----------------------|
| 0      | 97.1%  | 100%   | 100%   | 100%   | 100%                 |
| -3     | 88.0%  | 100%   | 98.5%  | 100%   | 100%                 |
| -6     | 76.2%  | 92.8%  | 97.6%  | 99.8%  | 100%                 |
| -9     | -      | 80.2%  | 96.3%  | 98.3%  | 99.5%                |
| -12    | -      | -      | -      | 90.0%  | 96.1%                |
| -15    | -      | -      | -      | 68.1%  | 77.9%                |

In reference [1], stacked auto-encoder was used to identify the radar emitter. When SNR is -6dB, the identify effect has been reduced obviously. Reference [2] used traditional CNN to identify the radar emitter. When SNR is -9dB, the identify effect was not good. Reference [3] proposed an improved CNN and the identify effect was better than [2]. Reference [4] used the VGG16 model to identify radar emitter, and the recognition rate is significantly improved in low SNR.
As a brand-new radar emitter identification method, the method in this paper has been further improved on the basis of literature [4]. Even in the case of low SNR (-15dB), recognition rate of SNN can still reach 77.9%. The confusion matrix is shown in table 2:

|       | FSK  | BPSK | CW   | LMF  | NLMF  |
|-------|------|------|------|------|-------|
| FSK   | 1844 | 31   | 98   | 6    | 21    |
| BPSK  | 108  | 1735 | 51   | 35   | 71    |
| CW    | 309  | 120  | 1390 | 88   | 93    |
| LMF   | 132  | 266  | 85   | 1419 | 98    |
| NLMF  | 187  | 249  | 77   | 87   | 1400  |

Table 2. Confusion matrix (SNR = -15dB)

After model training is completed, the spend time is 34.07s with 10,000 test image. The average time required for each image is about 3.4 ms, which can meet the requirements of real-time identify.

6. Conclusions
As a new type of network structure, the spiking neural network has extremely low power consumption and broad applications because it is close to the working mode of real neurons. Experiments result shows that the spiking neural network can identify radar emitter in real time and can achieve good results even in low signal-to-noise ratios.

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