LFM Signal Detection and Estimation Based on Deep Convolutional Neural Network

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***Abstract*—Linear frequency modulation (LFM) signal detection and estimation are important for radar, communication, or spectrum analysis etc.. As the generalized form of Fourier transform (FT), Fractional FT (FRFT) has good energy aggregation ability for LFM signal and can reflect the Doppler variation, which is suitable for LFM signal detection and estimation. However, it needs two-dimensional parameters searching and for multiple signals it requires searching one by one and easily affected by strong signals with poor resolution. In this paper, the convolutional neural network (CNN) is applied for replacing the FT and FRFT and used for signal frequency signal and LFM signal detection and estimation. The pre-trained CNN model can establish the relations among various single frequency signal or LFM signal and the two dimensional parameters domain. By simulation, it is found that the CNN based method can also achieve the function of FRFT and has the advantages of high precision and resolution. And it is proved that the CNN based method can achieve good recognition performance even at lower signal-to-noise ratio (SNR) combined with the denoising method. The proposed method would provide a novel solution for radar moving target detection, as well as speech intelligent signal processing, sonar signal processing, etc..**

I. Introduction

Linear frequency modulation signals are widely used in electronic information systems such as speech, radar, communication, sonar and electronic countermeasures, etc. [1]-[4]. The detection of unknown LFM signals plays an irreplaceable role in many fields such as radar target parameter measurement and electronic intelligence target recognition. In these applications, LFM signal detection is required. At present, the most widely used LFM signal detection method is based on time-frequency analysis. This method firstly uses time-frequency transform (short-time Fourier transform (STFT), Winger transform, ambiguity transform, etc.) to obtain the time-frequency distribution (TFD) of the signal, and then implements LFM signal detection via Radon transform or Hough transform, etc. [1]. The basic procedure of detection is feature extraction, i.e., the linear characteristics of the LFM signal in the time-frequency distribution. The drawback of these methods is that it needs first calculate the two-dimensional time-frequency distribution of the signal, and then perform the signal detection by means of the multi-dimensional peak searching, which would result in large computation burden. Moreover, the time-frequency resolution and integration performance would be different using different TFDs.

Fractional Fourier transform (FRFT) is an extension of the Fourier transform [5]. While retaining the properties and characteristics of the traditional Fourier transform, it adds new technical advantages. The FRFT with the rotational angle can better reflect the time-varying characteristic of a signal. With the development of radar signal detection technology, the LFM signal detection algorithm based on FRFT has been developed. The LFM signal is parameterized by using the energy aggregation of the LFM signal in the FRFT domain. However, it needs the two-dimensional parameters searching which would result in huge computational burden. Moreover, for multiple signals, it needs to search one by one, and the weaker signal would be easily affected by the strong one [6].

In recent years, deep learning theory accelerates the rapid development of intelligent processing and has been applied in the signal processing field [7]-[12]. For example, SAR image detection based on deep learning can be used for ground object recognition. Human body gesture recognition methods via deep learning and Doppler radar have been used for gesture command recognition, gait recognition, abnormal posture (such as drop, drowning) detection, etc. field. In addition, it has a very good application prospect in the recognition of high-resolution range images, micro-Doppler spectra and distance-Doppler spectra. Some popular deep learning models include convolutional neural network (CNN), recurrent neural network (RNN), and deep belief network (DBN). Among them, CNN is the most commonly used algorithm in computer vision. This kind of network can achieve high-precision classification, and no human intervention is required in the feature extraction process. Since the FT, FRFT or other time-frequency analysis methods can be regarded as a linear or nonlinear system, it is possible to replace them with the CNNs.

This paper attempts to find a novel solution for LFM signal detection and estimation via CNN, which can take advantage of the deep learning method in image processing and realize the intelligent extraction and recognition of the signal. The sampling sequence of LFM signals is classified by CNN, and the trained neural network is used to replace the FT and FRFT. The signal is classified by different frequencies, thereby realizing the detection and parameter estimation of the single frequency or LFM signal. Also, an example is given which uses the propose method for radar moving target detection. Section □ introduces the CNN model and the signal model of radar moving target. The flowchart of CNN-based LFM signal detection and parameter estimation method is given in

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Section □. The dataset construction for training and testing is also described. In Section □, simulations of radar moving target detection and parameters estimation are carried out and the results of the proposed method and traditional FT and FRFT methods are compared. The last section concludes the paper and gives future research direction.

II. CNN Model Construction and Modeling of Radar Moving Target Signal

A. Description of CNN Model

CNN is a popular algorithm in computer vision, especially in the field of two-dimensional image processing. CNN mainly includes multiple convolutional layers, pooled layers and fully connected layers, and finally uses softmax classification as the output layer. LeNet was one of the earliest convolutional neural networks that was originally used for digital handwriting recognition; AlexNet is a deeper and wider version of LeNet that extends LeNet's ability to learn more complex object and object levels. GoogLeNet is a "network in the network" whose idea is to reduce the computational burden while deep neural networks achieve higher levels of performance. These three networks are popular and representative networks in CNN, which is compared in detail in [11]. This paper employs commonly used AlexNet for training and testing and its structure is shown in Fig. 1.

B. Applications: Radar Moving Target Signal Model

We take radar moving target detection as an example for LFM signal detection and estimation. Radar moving target detection is an important issue both in military and civilian fields. The motion status is closely related to the signal's Doppler. And the Doppler spectrum of the target echo reflects the change of the target instantaneous velocity. Assuming that the radar and the target are in the same horizontal plane, the radar transmits an LFM signal

$$s_{\mathrm{t}}(t)=\mathrm{rect}\left(\frac{t}{T_{\mathrm{p}}}\right)\exp\left\{\mathrm{j}2\pi\left[f_{\mathrm{c}}t+\frac{1}{2}kt^{2}\right]\right\} \tag{1}$$

where $\mathrm{rect}(u)=\begin{cases}1, & |u|\le 1/2\\ 0, & |u|>1/2\end{cases}$, f_{c} is the radar carrier frequency, T_p is the pulse width, $k=B/T_p$ is the chirp rate of the transmitted signal, and B is the bandwidth, then the signal received by the radar at time t is expressed as

$$s_{\mathrm{r}}(t)=\sigma_{\mathrm{r}}\mathrm{rect}\left(\frac{t-\tau}{T_{\mathrm{p}}}\right)\exp\left\{\mathrm{j}2\pi\left[f_{\mathrm{c}}(t-\tau)+\frac{k}{2}(t-\tau)^{2}\right]\right\} \tag{2}$$

where σ_{r} is the scattering cross-sectional area of the target, $\tau=2r_{\mathrm{s}}(t_{\mathrm{m}})/c$ is the time delay, c is the speed of light, $r_{\mathrm{s}}(t_{\mathrm{m}})$ is the line-of-sight distance between the radar and the target, and t_{m} is the slow time between the pulse and the pulse. After the echo is demodulated and pulse compressed, the above equation is rewritten as [2]

$$s_{\mathrm{PC}}(t,t_{\mathrm{m}})=A_{\mathrm{r}}\mathrm{sinc}\left[B\left(t-\tau\right)\right]\exp\left(-\mathrm{j}2\pi f_{\mathrm{c}}\tau\right) \tag{3}$$

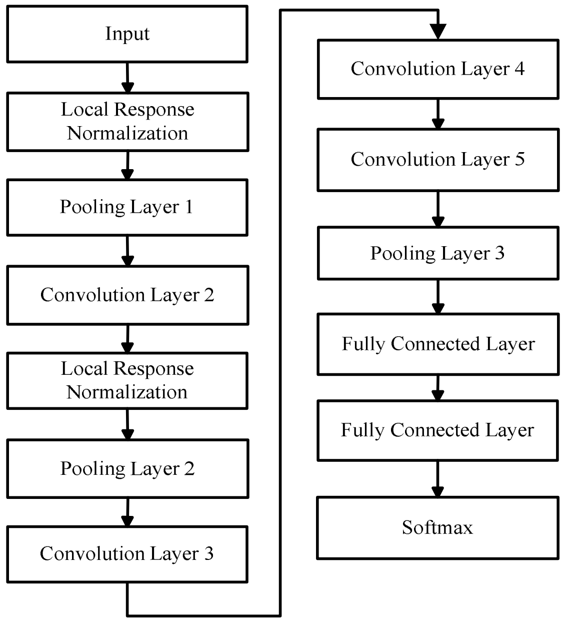


Fig. 1 Structure of AlexNet

The distance of the target is a polynomial function of time, which can be obtained by Taylor series expansion

$$r_{\mathrm{s}}(t_{\mathrm{m}})=r_0-vt_{\mathrm{m}}-\frac{1}{2!}v't_{\mathrm{m}}^2-\frac{1}{3!}v''t_{\mathrm{m}}^3-\cdots,\ t_{\mathrm{m}}\in[-T_n/2,T_n/2] \tag{4}$$

where v is the target radial velocity, and T_n is the observation time. Only the first four terms of the above formula are retained as an approximation of the observation distance, then the above formula is rewritten as

$$r_{\mathrm{s}}(t_{\mathrm{m}})=r_0-v_0t_{\mathrm{m}}-at_{\mathrm{m}}^2/2-gt_{\mathrm{m}}{}^3/6 \tag{5}$$

where r_0 is the distance between the target and the radar, and v_0, a and g are the components of the target initial velocity, acceleration, and jerk (acceleration change).

In this paper, we only care about the uniform motion and the acceleration, and the Doppler spectrum of uniform shifting motion is shown in (6), which has the characteristics of constant function. The variable acceleration motion Doppler spectrum is as shown in (7) and has the characteristics of a linear function.

$$f_{\mathrm{d}_1}=2v_0/\lambda \tag{6}$$

$$f_{\mathrm{d}_2}=2(v_0+a_st_{\mathrm{m}})/\lambda \tag{7}$$

where λ is the wavelength and a_s is the target acceleration.

Then the relationship between the initial frequency f_0 and chirp rate μ with the target motion velocity v_0 and acceleration a_s is established. The signal model of radar moving target can be expressed in (10).

$$f_0=2v_0/\lambda \tag{8}$$

$$\mu=2a_s/\lambda \tag{9}$$

$$s(t_m)=A_0\exp[\mathrm{j}(2\pi f_0t_m+\pi\mu t_m^2)] \tag{10}$$

During short observation time, the moving target returns can be approximated as an LFM signal.

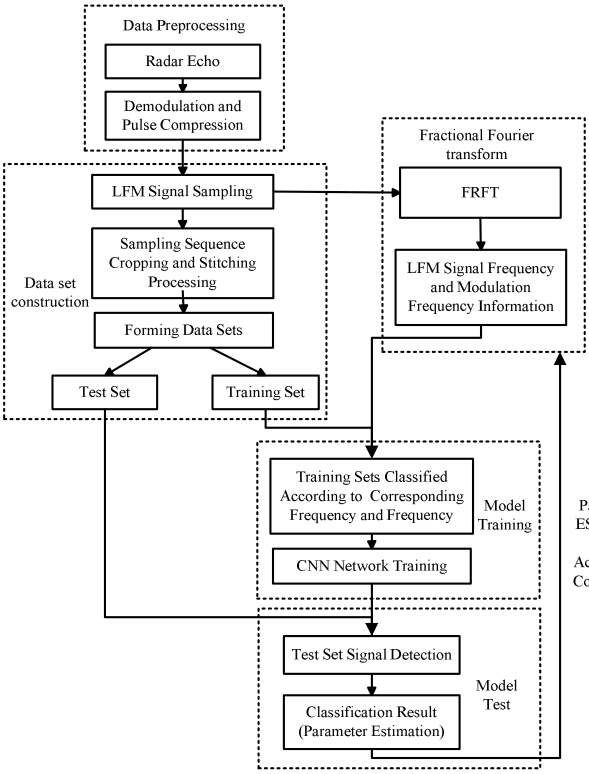


Fig. 2 Algorithm flowchart

III. CNN-BASED LFM SIGNAL DETECTION AND PARAMETER ESTIMATION

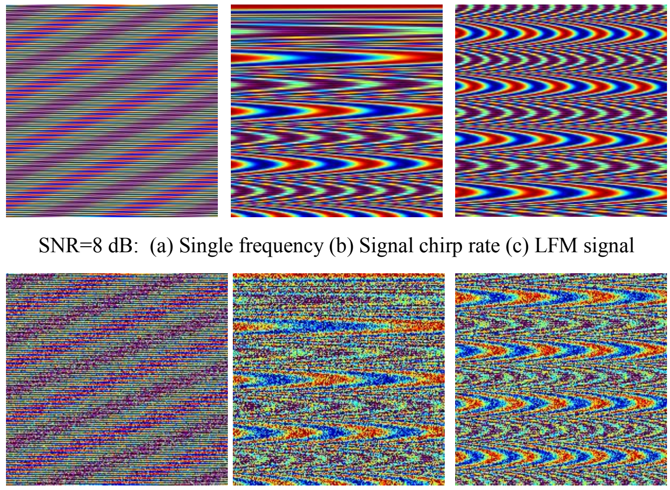
A. Algorithm Flowchart Description

The proposed CNN-based LFM signal detection and estimation method mainly includes five steps: 1) Data preprocessing; 2) Dataset construction; 3) FRFT labeling; 4) Model training; 5) Model testing (parameter estimation). The algorithm flowchart is shown in Fig. 2.

Firstly, the radar echo is demodulated and pulse compressed. Then, the preprocessed LFM signal is sampled, and the sampled signal is a set of one-dimensional sequences. We cut the one-dimensional sequence into equal-length segments at regular intervals, and splicing from top to bottom in chronological order to form one dimensional matrix, which is used as samples for training set and test set. At the same time, all the LFM signal sample sequences are calculated by FRFT to obtain real initial frequency and frequency modulation (chirp rate) information. Then the training set is classified by CNN according to the obtained frequency and chirp rate. Finally, the trained model is tested with the test dataset to realize the parameter estimation of LFM signal.

B. Dataset Construction

The dataset used in this paper consists of a one-dimensional signal sampling sequence. We cut the one-dimensional sequence into equal-length segments at regular intervals, and splicing them from the top to the bottom in chronological order to form a two-dimensional matrix. Feature learning is performed using CNN and used for detection and classification.



SNR=8 dB: (a) Single frequency (b) Signal chirp rate (c) LFM signal

SNR=0 dB: (d) Single frequency (e) Signal chirp rate (f) LFM signal

Fig. 3 Examples of dataset images with different parameters and SNRs

The data used in model training and testing is divided into three kinds. The first kind is the single-frequency signal, and the corresponding target motion state is uniform motion. The second kind is signal chirp rate signal, and the corresponding target motion is acceleration with initial velocity 0 m/s (acceleration 1). The third kind is the LFM signal, and the corresponding target motion is acceleration with an initial velocity not being zero (acceleration 2). Supposing the radar working in the S-band (3 GHz) detects the marine target, e.g., boat or ship, and the signal parameters can be derived according to the formulas (8) and (9). The parameters of target motion and related radar signal are show in Table 1 and Table 2 respectively.

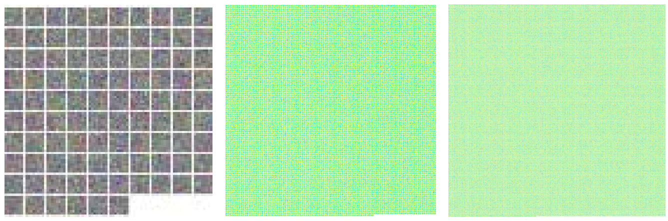
TABLE I. MARINE TARGET MOTION PARAMETERS

Motion types	Speed (m/s)	Acceleration (m/s^2)
Uniform motion	[0, 15]	0
Acceleration 1	0	[0, 5]
Acceleration 2	[0, 15]	[0, 5]

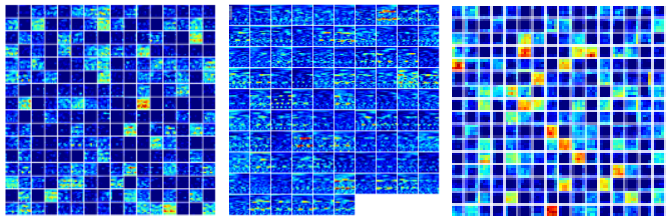
TABLE II. RADAR SIGNAL PARAMETERS

Signal types	Frequency (Hz)	Chirp rate (Hz/s)
Single frequency	[0, 300]	0
Single chirp rate	0	[0, 100]
LFM signal	[0, 300]	[0, 100]

The target's frequency is divided into 300 categories, the resolution is 1 Hz, and the chirp rate is divided into 100 categories, the resolution is 1 Hz/s. The number of sampled signal points is 40000. The sequence is cut at intervals of 200 points, and then chronologically from top to bottom. Stitch to form a 200×200 matrix and transform the matrix into a color map. In the case of different signal-to-noise ratios (SNR),



(a) Kernel of conv1 (b) Kernel of conv2 (c) Kernel of conv5



(d)Feature map of conv1 (e) Feature map of conv2 (f) Feature map of conv5
Fig. 4 Data characteristics of each convolution layer in AlexNet for the signal in Fig. 3(a).

according to the above resolution classification, single-frequency signals and monotone signals are classified into 300 classes and 100 classes, and LFM signals are classified into 5000 classes, each of which consists of 150 images. Among these, 125 are for training and 25 for testing, with a total of 810,000 images in the entire data set.

Fig. 3 shows some examples of the datasets. From left to right, the images are the single frequency signal, the single chirp rate signal, and the LFM signal, respectively. The upper and lower lines represent the higher signal-to-clutter ratio (SNR) (8 dB) and the lower SNR (0 dB). Fig. 4(a) to Fig. (c) are the convolution kernels of the first, second, and fifth convolutional layers of AlexNet for the signal in Fig. 3(a). And Fig. 4(d) to Fig. 4(f) are the feature maps of the convolutional layers correspondingly. It can be seen that the neural network can learn the detailed features of the signal in different convolutional layers, thereby facilitating the identification of different types of signals.

C. LFM Signal Detection and Estimation in Noise Background via Wavelet Denoising and CNN

Since the dataset image generated by this method only contains the amplitude information of the signal and does not contain the phase information, it can't achieve time accumulation compared with FRFT, so it is very sensitive to SNR especially for low SNR. In order to improve recognition rate of the training model and the detection performance in noise background, we employ wavelet analysis and design a denoising method before sending to CNN for learning.

Wavelet analysis has the characteristics of low entropy, multi-scale, de-correlation, and flexibility of selection [13][14]. The above characteristics make it is good at processing non-stationary signals and denoising. The basic idea of wavelet threshold denoising proposed by D. L. Donoho is that after the signal is transformed by wavelet, the wavelet coefficient generated by the signal contains important information of the signal. After the mixed signal is decomposed by wavelet, the wavelet coefficient of the signal

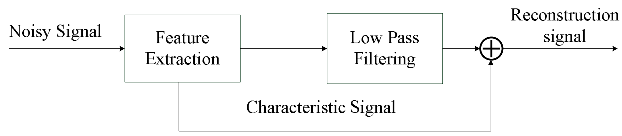


Fig. 5. Wavelet denoising process.

is large, while the wavelet coefficient of noise is small. By selecting an appropriate threshold, the wavelet coefficients bigger than the threshold are considered to be signal-generated and should be retained. On the contrary, it is considered to be noise generated. Thereby achieving the purpose of denoising. The wavelet denoising process is shown in Fig. 5.

IV. SIMULATION RESULTS AND ANALYSIS

This paper employs AlexNet for training and testing using Python2.7, VS2013, CUDA7.5, cudnn5.1, Caffe environment architecture. The computer is configured as a dual E5 processor, the graphics card NVIDIA Quadro M2000, 24GB memory. According to the convergence of the loss value during the training process, the model training parameters are as follows:

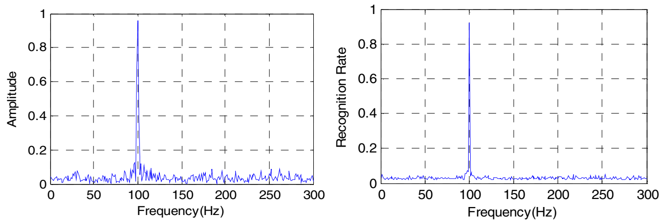
- The number of iterations is 30;
- The parameter solving algorithm adopts the stochastic gradient descent (SGD);
- The descent strategy adopts gradient descent;
- The initial learning rate is 0.01;
- The step size is 33%;
- The rate of change is 0.1.

After testing with the CNN-based method, the average recognition probabilities of the three kinds signals with SNR=5dB are obtained, which are given in Table 3. Moreover, the signal detection performance of FRFT is compared as well by Monte Carlo trials. 10^6 times of experiments are carried out to obtain the detection probability. The results show that performance of CNN-based method for the three kinds of signals are quite similar with the traditional FRFT method. It indicates that the deep CNN can act the same function of FT or FRFT while it is more flexible without parameters searching. The more datasets training, the more accurate of the parameters estimation.

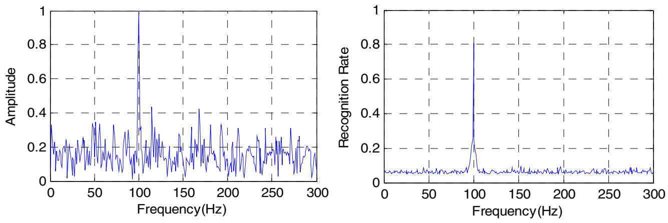
TABLE III. TEST RESULTS COMPARISON OF FRFT AND THE PROPOSED METHODS (SNR=5DB)

Signal Type	Single frequency signal	Single chirp rate signal	LFM signal
Detection probability (FRFT)	94.6%	94.11%	91.45%
Recognition rate (CNN)	97.91%	94.35%	90.58%

As for the recognition rate of each signal classification, we use the 100th classification of the single-frequency signal as an example and compare with the FFT spectrum, which is shown in Fig. 6 and Fig. 7. The recognition rate is the value with different classifications. It can be found from the two figures that the results are basically the same, and it is

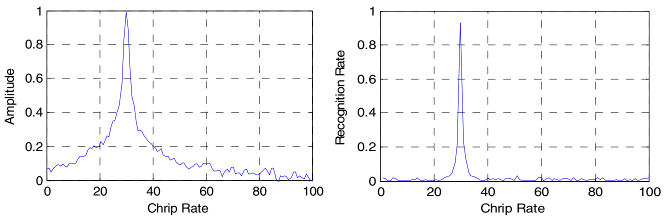


SNR=8dB: (a) FFT spectrum(b) Frequency identification probability

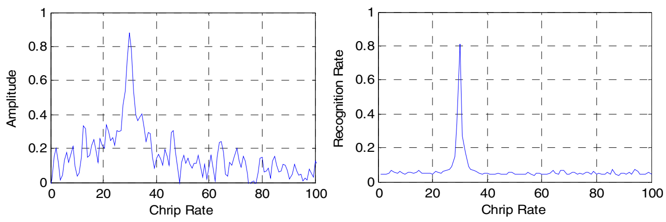


SNR=0dB: (c) FFT spectrum (d) Frequency identification probability

Fig. 6. Comparison between the proposed method and FFT at different SNRs



SNR=8dB: (a) FRFT spectrum (b) Chirp rate identification probability



SNR=0dB: (c) FRFT spectrum (d) Chirp rate identification probability

Fig. 7. Comparison between the proposed method and FRFT at different SNRs

basically concluded that CNN training can effectively replace FFT calculation. And one more advantage of CNN-based method is that it has no sidelobes as the result of FFT, which is useful and helpful for radar target detection. Also, comparing the performance at lower SNR, i.e., Fig. 6 (c) and Fig. 6(d), the CNN-based method has better anti-noise performance and it is robust for different SNRs. This is because it can learn the signal property for various scale features, which would be helpful for distinguishing from the noise. We can obtain the similar conclusions for the FRFT and CNN based method, which is shown in Fig. 7. Both the recognition performance and resolution are improved via the proposed method. Therefore, the CNN-based method can achieve high-resolution estimation of parameters and can act the same function as FT and FRFT.

In addition, in order to analyze the influence of SNR on the recognition rate of the proposed method, based on the previous signal model, white noise of different intensities is added, and the signal recognition simulation under different SNRs is performed, which is shown in Fig. 8. It can be seen from the figure that if the SNR is higher than 0 dB, the

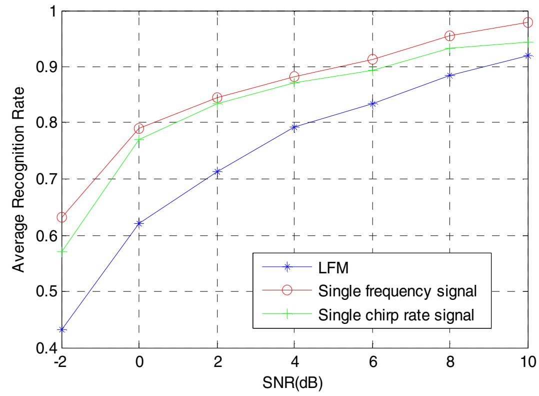


Fig. 8. Average recognition rate at different SNRs via CNN.

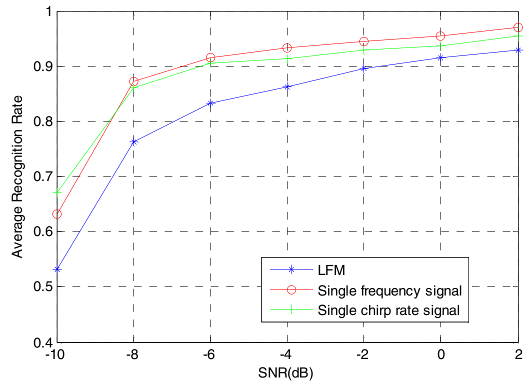


Fig. 9. Average recognition rate at different SNRs via CNN after wavelet denoising.

propose CNN based method can achieve a satisfied result for all the kinds of signal. And when SNR>5dB, the recognition rate is almost 95%. However, the proposed method is still affected by the noise in case of lower SNR. Then, Fig. 9 gives the average recognition rate at different SNRs after wavelet denoising. Compared with Fig. 8 and Fig. 9, the Average recognition rate is improved by about 30% for the LFM signal at SNR=0dB, and even at the SNR=-8dB, it still can get a satisfied recognition rate. The above results verify the correctness of theoretical analysis.

V. CONCLUSIONS

In this paper, a CNN-based method for detecting and parameter estimation of LFM signal is proposed. It makes full use of the advantages of deep neural network feature learning ability. Datasets of three kinds of signals, i.e., signal frequency signal, signal chirp rate signal, and LFM signal, under different SNRs are built for training and testing. The trained CNN is used to replace the FT and FRFT. Simulations results indicate that in case of higher SNR, the recognition rate of the three kinds of signals are all above 90%. Moreover, the CNN-based method dose not introduce the sidelobes and has higher resolution, which is quite promising for radar target detection. For future research, we will find solution to improve the accuracy of the detection and parameter estimation and carry out numerical experiments under complex environment, such as clutter background.

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