Signal Modulation Recognition Method based on Time-frequency Image

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Abstract. Signal modulation classification is an important technology for signal processing, in order to get higher recognition accuracy at low signal-to-noise ratios, this paper proposed a modulation recognition algorithm which combines CNN and time-frequency analysis methods. The method's steps are as following, first, make the SPWVD transforms to the digital signals to obtain corresponding time-frequency images. Then, use image processing method to enhance the obtained images, such as image gray processing, perform the grayscale equalization and binarization the images. After that, the pictures are inputted into the CNN network for classification and recognition. The experimental results show that the recognition rate can achieve 90.44% at 0dB.

Keywords: Modulation recognition, time-frequency, CNN, image processing.

1 Introduction

Wireless communication has a fixed spectrum allocation strategy. As the requirements of wireless spectrum bandwidth continue to increase, researchers need to make full use of existing wireless spectrum resources to avoid signal problems faced by wireless networks[1]. As we all know, modulation identification is a method of optimizing spectrum allocation in cognitive radio monitoring, which plays a vital role in both military and civilian use[2], and its purpose is to provide wireless communication without almost any prior knowledge. The signals are classified and identified[3].In the military field, modulation identification is mainly used in electronic warfare to recover intercepted enemy signals and obtain corresponding intelligence. In the civil field, modulation identification is mainly used for spectrum monitoring and interference identification[4]. Spectrum resources are the most precious resources in modern wireless communications. The shortage of spectrum resources also causes some institutions or individuals to illegally occupy allocated frequency bands, which will seriously interfere with the normal communications of legitimate users and even normal users, besides its can cause security issues.

There are two main methods for signal modulation classification, one based on likelihood and characteristics. However, most likelihood methods require parameter estimation, which complicates the calculation, so methods based on easy-to-implement features have been widely used. So far, various feature-based methods[5-7] have been proposed. These features are based on spectrum analysis[8], time-frequency distribution[9], wavelet transform[10], constellation maps[11, 12], and so on.

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The authors in [3] used a combination of semi-supervised learning[13] method and GAN network to modulate and identify signals. Experiments show that this method can achieve better classification performance with lower signal-to-noise ratio. In [14] used a generative adversarial network to obtain higher accuracy of classification for communication signals. The experimental results show that in the ACGAN-based data set, the classification accuracy of wireless signals is improved by 0.1~6%. In order to be able to accurately extract the individual characteristics of the radiation source in a complex wireless communication environment, a method for feature extraction of individual characteristics of communication signals based on fractal complexity is described in [15]. This method can reduce the signal noise compare the communication signals accurately.

2 Principle analysis

2.1 Short Time Fourier Transform

When the stationary signal is analyzed, the signal is recorded or observed at any time, and the Fourier transform is performed. The result obtained is same and it is a constant which is no relationship with time. When analyzing non-stationary signals, a time-frequency joint analysis method is required. The simplest and most direct one is the short-time Fourier transform (Short Time Fourier Transform, STFT). The STFT of the time signal can be defined as:

$$\begin{aligned} STFT(t,f) &= \int_{-\infty}^{+\infty} x(\tau) g(\tau - t) e^{-j2\pi f\tau} d\tau \\ &= \langle x(\tau), g_{t,f}(\tau) \rangle \end{aligned} \tag{1}$$

where $\langle \bullet \rangle$ is the inner product, t,τ is frequency factor. $g_{t,f}(\tau) = g(\tau - t)e^{j2\pi f\tau}$, and the window functions satisfied $\|g(t)\| = 1$, $\|g_{t,f}(\tau)\| = 1$. The basic thinking of STFT is to build a window function $g(t)$,which can slide along the time axis and the size of it was fixed, when observe the local frequency character of the signal through this window function, which can get a group of Fourier transform, these Fourier transform are character of the time-frequency. But the type of window function has the direct influence for the effect of the time-frequency, it can be shows for the two aspects: first is the type of the window function, it is not difficult to choose a fit window function for a certain signal, but when deal with the overlap signal, this can be difficult; on the other side, the size of the window is also difficult, when analysis the fast signal, the time resolution should be improved, but when analysis the slow signal, the frequency resolution should be improved.

The uncertainty principle defines the constraint relationship between the width and bandwidth of a given signal, that is, the product of the multiplication of the two is greater than a fixed value, and it is impossible to reach infinitely small at the same time, which means that time resolution and frequency resolution are a contradiction.

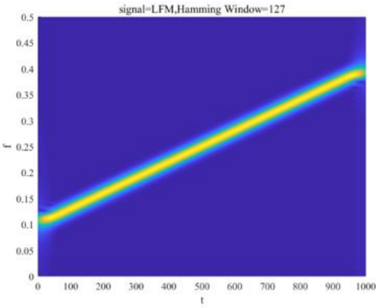


Fig. 1. LFM’s STFT time-frequency image for Hamming=127.

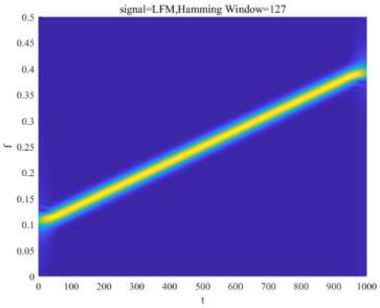


Fig. 2. LFM’s STFT time-frequency image for Hamming=517.

Figure 1 and Figure 2 show that there is an obvious contradiction between time resolution and frequency resolution. There are two ways to either get rid of the constraints of the window function or try to make the time resolution and frequency resolution meet the requirements for the signal. The requirements of analysis make it achieve the effect of adaptive adjustment.

2.2 Wigner-Ville Distributions

One of the earliest time-frequency representation method is called WVD(Wigner-Ville Distributions, WVD), which has good time-frequency representation methods. WVD has goodtime-frequency aggregation, high time resolution and frequency resolution, and it is simple to calculate. The WVD of signal $s(t)$ can be defined as,

$$W(t, f) = \int_{-\infty}^{+\infty} s\left(t+\frac{\tau}{2}\right) s^*\left(t-\frac{\tau}{2}\right) e^{-j2\pi f\tau} d\tau \tag{2}$$

Using the signal itself as a window function to perform a STFT can be simulated, which can overcome the shortcoming of the STFT. The window function has some kind of adaptability to the signal. But WVD is not good for the superimposed signal $x(t) = x_1(t) + x_2(t)$, its WVD is

$$\begin{aligned} WVD_x(t, f) &= WVD_{x_1}(t, f) + WVD_{x_2}(t, f) \\ &+ WVD_{x_1,x_2}(t, f) + WVD_{x_2,x_1}(t, f) \end{aligned} \tag{3}$$

where, $WVD_{x_1,x_2}(t, f) = \int_{-\infty}^{+\infty} x_1\left(t+\frac{\tau}{2}\right) x_2^*\left(t-\frac{\tau}{2}\right) e^{-j2\pi f\tau} d\tau$, which means when dealing with the superimposed signal, WVD can’t direct reflect the time-frequency’s character, it needs further processing.

2.3 Pseudo Wigner Ville Distribution

In order to solve the bilinear problem of WVD, the WVD is smoothed in the frequency domain as,

$$PWVD_s(t,\omega) = \int_{-\infty}^{+\infty} h(\tau) s\left(t+\frac{\tau}{2}\right) s^*\left(t-\frac{\tau}{2}\right) e^{-j\omega\tau} d\tau \tag{4}$$

where the function is defined as $h(\tau)$. However, PWVD(Pseudo Wigner Ville Distribution, PWVD) can just smooth the direction of variation of τ 's cross terms and reduce the resolution of its.

2.4 SmoothPseudo Wigner Ville Distribution

If add the window and cut from both of the direction of variation of t and τ, if this way the method can cut down the cross term of the two directions to get SPWVD(SmoothPseudo Wigner Ville Distribution, SPWVD),

$$SPWVD_s(t,\omega)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} g(u)h(\tau)s\left(t-u+\frac{\tau}{2}\right)s^*\left(t-u-\frac{\tau}{2}\right)e^{-jw\tau}dud\tau \tag{5}$$

For that the WVD distribution has a high time and frequency resolution, it can be used to describe the signal. However, due to its bilinear, there is a cross term in the middle of the signal term, which generates false signals, which causes trouble to the signal analysis. Therefore, STFT, WVD, PWVD and SPWVD are simulated, and the suppression performance of cross terms by different algorithms is shown in Figure 3 to Figure 5.

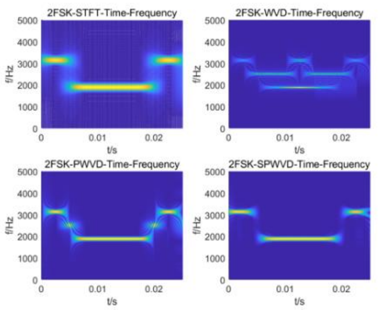


Fig. 3. Time-frequency diagram of the four transformations of the 2FSK signal

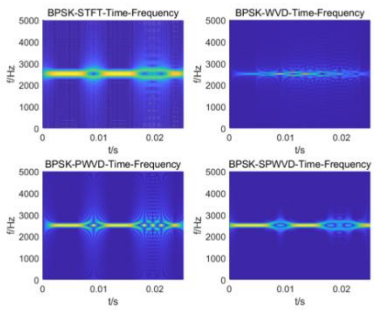


Fig. 4. Time-frequency diagram of the four transformations of the BPSK signal

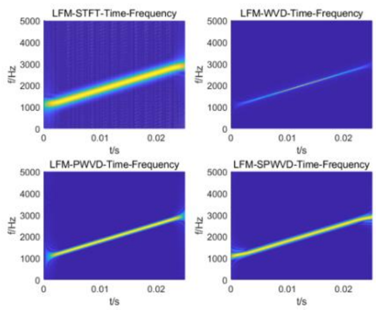


Fig. 5. Time-frequency diagram of the four transformations of the LFM signal

2.5 Image Processing

Most image processing methods are defined based on grayscale or binary graphics, so the SPWVD time-frequency image can be transform into the grayscale image. The Figure 6 and Figure 7 show the comparison of the time-frequency image before and after the grayscale change.

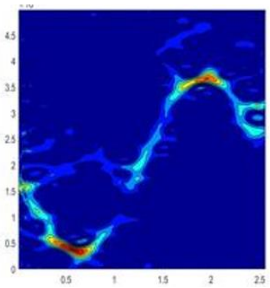


Fig. 6. NLFM's SPWVD time-frequency image

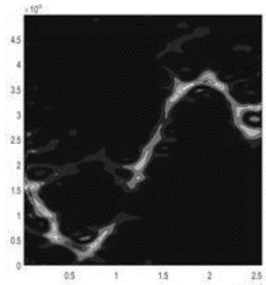


Fig. 7. NLFM's time-frequency grayscale change

In order to make the image can achieve the effect of removing noise and cross terms, the image enhancement technology is used below. The quality of the graphics directly obtained by time-frequency transformation or other methods are not ideal, this is for that the noise and interference signals are often affected in the process of obtaining graphics. It is necessary to improve the quality of images to get the better analyze of images. A common method is to the enhancement of images. The most important part of this technology is highlights features of interest in images, and cut down the features which are not wanted.

Due to the noise and other interference, the grey-scale images obtained by time-frequency technology are always not clearly. One way to enhance graphics is the gray-scale histogram transformation. Its main task is to modify the gray-scale values to make the graphics achieve a uniform effect. The gray level histogram is defined as the correspondence between each gray level (normalized gray level) in the graph and the frequency of the gray level. The probability of the occurrence of any $k-th$ gray level is defined as,

$$h_k = \frac{n_k}{N} \tag{6}$$

where, n_k is the number of the $k-th$ gray level appear, N is the total of the image gray level. The gray histogram of **Figure 8** is shown in **Figure 9**.

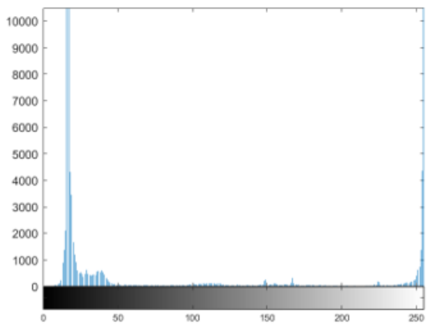


Fig. 8. The diagram of the grayscale histogram

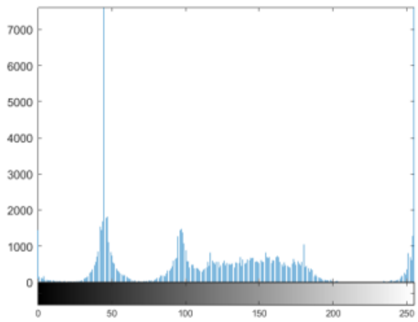


Fig. 9. Histogram of transformation image

Fig. 10. The image after histogram transformation

Fig. 11. Binary image of the signal

Observing from the Figure 8, the gray level of the image is mostly concentrated between 0 and 50, and the gray value of this area represents the background part of the image, the gray level of the signal is higher, but its proportion in the gray histogram is smaller. For that the signals (especially some weak signals) can be easily masked on the image. Changing the shape of the histogram is to fill the part with the smaller gray level with the part with the larger gray level to achieve the effect of artificially supplementing the signal energy. In fact, a common method for changing the shape of a histogram is equalization of the histogram. The image and its histogram after histogram transformation are shown in Figure 9 and Figure 10.

The grayscale image after the histogram transformation improves the contrast of the signal, and the signal part can be more clearly displayed on the time-frequency image, which increases the brightness of the signal to a certain extent and enhances the viewability of the signal. However, on the other hand, the noise and residual cross terms are also more apparent in front of the image. In order to improve the contrast of the signal, convert the image into a binary image which was shown in Figure 11. The binarization processing steps are as follows,

(1) Sum all pixels on the grayscale image and average them.

$$thresh = \frac{1}{N}\sum_{k=1}^{N} h(k) \tag{7}$$

where, N is number of points in the grayscale image, $h(k)$ is the grey value of the image.

(2) The gray value in the grayscale image is judged. If the grayscale value is greater than , the judgment is 1, otherwise the judgment is 0.

After the binarization process, the signal can be clearly displayed, and the cross-term interference left by the SPWVD time-frequency transform is effectively removed.

3 Experiment

Modulation identification of six types of signals LFM, NLFM, BPSK, 2FSK, 2ASK signals, the range of snr is -2dB to 10dB, and the step is 2dB. The length of these five signals is 256, and the sampling frequency is 1000kHz. Each type of signal generates 300 signals in each modulation mode.The flow chart of the simulation experiment is shown in Figure 12.

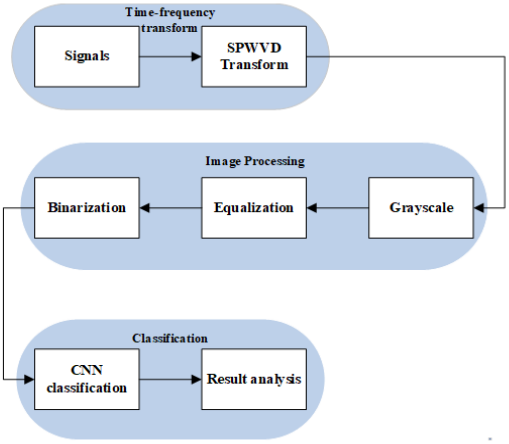
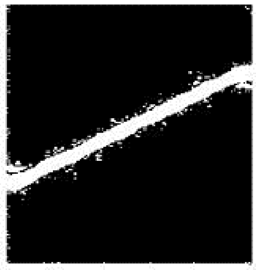


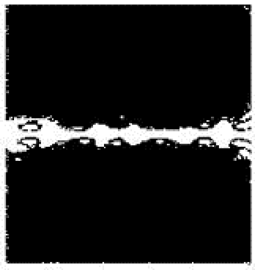
Fig. 12. Algorithm flow chart for proposed method.

The main steps are as following: First, input the five kinds of signals, then make SPWVD transform to get their time-frequency image. By processing the time-frequency diagrams of grayscale, equalization, and binarization, time-frequency diagrams of the five signals in Figure 13 after image processing are obtained.

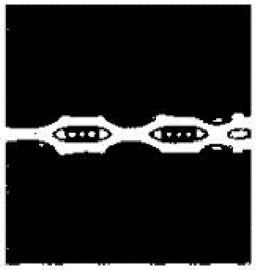


(a)LFM

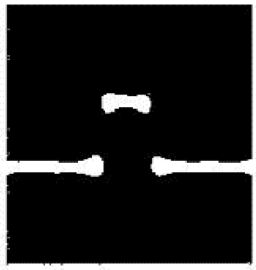
(b)NLFM



(c)2ASK



(d)BPSK



(e)2FSK

Fig. 13. Time-frequency diagram of the four transformations of the LFM signal

Then make 300 images for each signal, 70% of the images are test set and else are validation set. Put then into the CNN(Convolutional Neural Networks, CNN). The CNN network which used in this paper is based on the GoogleNet, it was proposed by Christian Szegedy. Before GoogleNet, the AlexNet and VGG are both obtain better training result by increasing the depth of the network, however the increase of the number of the levels can bring many bad effects. In this paper's method use the inception to get better classification accuracy. The inception model which was uesd in this paper was shown in Figure 14.

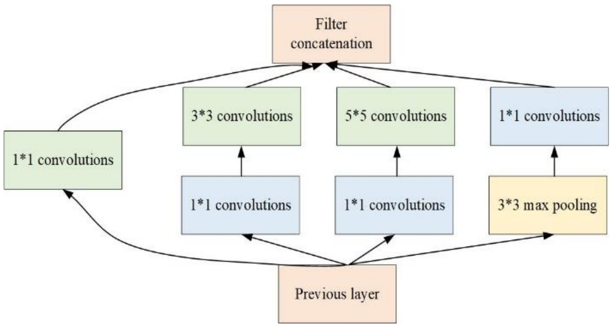


Fig. 14. The architecture of the Inception.

The simulation experiment was based on MATLAB 2019a, after classification in the CNN, the result is shown below. Figure 15 is the confusion matrix of the signal classification results at 0dB. The average classification accuracy can be calculated as,

$$Accuracy = \frac{numSignalAccuracy}{numSignals} \tag{8}$$

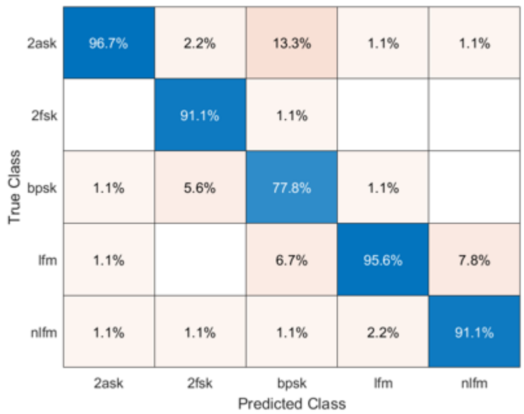


Fig. 15. Confusion matrix for signal classification results at 0dB.

where, $numSignalAccuracy$ is the total number of the signal accuracy, $numSignal$ is the number of the kinds of signal. The average classification accuracy can be calculated as, of 5 signals is 90.44%.

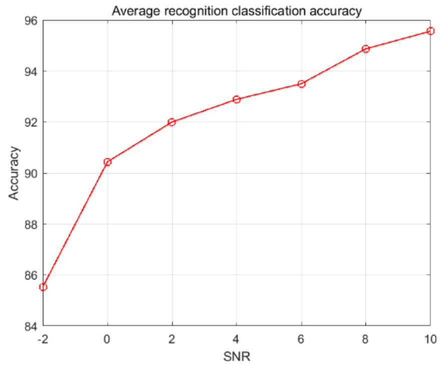


Fig. 16. Average classification accuracy rate

In order to analyze the classification performance of the proposed algorithm more intuitively, the average classification accuracy rate is visualized as shown in Figure 16. With the increase of the SNR, the signal can get better and better classification accuracy. In order to analyze the classification effect of the method in this paper, the accuracy curve of the signal recognition and classification results under different signal-to-noise ratios is shown in Table 1.

Table 1. Recognition and classification results

SNR	*2ASK*	*2FSK*	*BPSK*	*LFM*	*NLFM*	*Average*
-2	81.1%	82.2%	90.0%	92.2%	82.2%	85.54%
0	96.7%	91.1%	77.8%	95.6%	91.1%	90.44%
2	85.6%	94.4%	94.4%	95.6%	90.0%%	92.00%
4	95.6%	90.0%	95.6%	90.0%	93.3%	92.89%
6	81.1%	96.7%	98.6%	98.9%	92.2%	93.50%
8	93.3%	97.75%	87.8%	97.7%	97.8%	94.87%
10	96.7%	94.4%	98.9%	92%	95.6%	95.56%

4 Conclusion

The time-frequency transform of the received signal is analyzed to obtain the corresponding time-frequency map. The image processing can improve the texture details of the time-frequency map. Then use the neural network to classify and recognize the processed time-frequency map. In this method can obtain better classification results. However, the time-frequency map obtained after SPWVD transformation is still subject to the interference of cross terms. In the subsequent research, the time-frequency transformation method of the signal needs to be further improved to achieve the purpose of improving the accuracy of signal classification.

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