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MULTI CHANNEL ELECTRONIC COMMUNICATION SIGNAL PARAMETERS BASED ON NONLINEAR PHASE PRINCIPLE MODULATION AND DEEP LEARNING

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Abstract. In order to solve the problem of high sampling rate and large number of sampling points required by current phase modulation signal parameter estimation methods, a parameter modulation method for multi-channel electronic communication signals based on nonlinear phase principle and deep learning is proposed. Firstly, classify and introduce the modulation methods, and propose a new algorithm for identifying instantaneous feature parameters. The author conducted nonlinear phase principle modulation recognition on seven typical digital signals: 2ASK, 4ASK, 2FSK, 4FSK, 2PSK, 4PSK, and 16QAM. Using the author's algorithm, experiments were conducted on the recognition of seven digital nonlinear phase modulation signals under different signal-to-noise ratios. As can be seen from the results, when the signal-to-noise ratio is greater than or equal to 10dB, the recognition accuracy of the seven digital nonlinear phase modulation signals can reach 100%, verifying that the new algorithm proposed by the author improves the recognition accuracy.

Key words: Nonlinearity, Phase principle modulation, Communication signal, characteristic parameter

1. Introduction. Automatic modulation recognition technology is a very important topic in the field of non cooperative communication signal processing research. The task of modulation recognition for communication signals is to identify signals without sufficient or complete prior knowledge, by performing various processing on the received signal, the modulation method and related modulation parameters used in the signal can be accurately determined[1]. For the signal receiving end, determining the modulation method of the received signal and correctly demodulating the signal is a necessary prerequisite for restoring the original signal. The study of automatic modulation recognition technology for signals has significant practical value in both military and civilian fields. The practical value of modulation recognition technology is mainly reflected in: In the military field, successfully determining the modulation mode of the signal is a prerequisite for achieving reconnaissance and interference of enemy communication. Knowing the modulation method of enemy signals can estimate some useful parameters, in order to conduct targeted reconnaissance and electronic interference on enemy communication; In the civilian field, the task of radio management work in the communication management department is to monitor whether legitimate radio stations comply with the working parameters assigned by the management department during the communication process, while listening for interference from illegal radio stations to ensure the normal communication of legitimate radio stations. The most crucial technology to achieve these non cooperative communication tasks is modulation recognition technology. There are two methods for modulation recognition of wireless communication signals: One is manual judgment, and the other is machine automatic recognition. Early modulation recognition methods used a set of demodulators with different modulation methods, the received signal is downconverted and input into each demodulator to obtain an observable signal, which is then judged by the operator based on information such as time-domain waveform, signal spectrum, instantaneous amplitude, instantaneous frequency, and instantaneous phase [2,3]. The recognition method of manual judgment requires experienced operators. Due to the subjective factors involved in the judgment process, the judgment results will vary from person to person, and the modulation types that can be recognized by manual judgment will be very limited. And automatic modulation recognition technology can solve the above problems.

The ultimate goal of automatic modulation recognition technology is to develop a machine that can recognize as many modulation modes as possible without any prior knowledge and low signal-to-noise ratio. We hope that the less prior knowledge there is in modulation recognition, the better, or the more "blind" the

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modulation recognition algorithm is[4,5]. However, in the actual research process of modulation recognition technology, researchers will more or less add some prior knowledge, such as only studying digital modulation recognition, which means that they already know that the received signal is a digital signal, not an analog signal.

2. Literature Review. Radar signal recognition is an important aspect of electronic reconnaissance, which refers to the process of matching the features of the received signal emitted by the radar signal source with the pre accumulated signal features to confirm the signal modulation method. Radar signal recognition usually includes: Intentional modulation recognition and unintentional modulation recognition of radar signals, target recognition of radar signal source platforms, and estimation of recognition credibility [6]. At present, Western countries led by the United States are in a leading position in radar signal recognition technology, but due to their military confidentiality, they have limited access to information. As far as we know, the main algorithms for radar signal recognition include time-frequency analysis, spectral correlation, time-domain auto-correlation, wavelet transform, digital intermediate frequency, and time-domain cepstrum. The time-domain cepstrum method extracts modulation features and related modulation parameters by calculating the cepstrum of the signal. This method requires various transformations, requires a large amount of computation, is difficult to implement in hardware, and has low accuracy, so its practical application value is not significant. The digital intermediate frequency method can comprehensively recognize radar signals, with the increasing processing speed of DSP chips, it is a promising technology, however, the relevant technology is not yet very mature and requires a lot of research. The advantage of spectral correlation method is that it has good resolution, but the actual environment is complex and the received signal length is limited, resulting in low recognition accuracy. The time-frequency analysis method and wavelet transform method are newly developed and highly effective tools for processing non-stationary signals in recent years [7]. The time-frequency analysis method is a two-dimensional joint analysis of the time-domain and frequency-domain characteristics of a signal, the real-time frequency analysis method can simultaneously describe the energy density of a signal at different times and frequencies, and can effectively describe the local characteristics of the signal, in recent years, it has received increasing attention. The wavelet transform method is also a time-frequency analysis method, which has the characteristics of multi resolution analysis and can characterize the local characteristics of the signal. The signal has high frequency resolution and low time resolution in the low frequency range, while it has low frequency resolution and high time resolution in the high frequency range, therefore, applying wavelet transform to the signal can obtain different details. And different radar signals have different detailed features, which can be used to identify radar signals [8]. Researchers have been striving to find fast and efficient automatic recognition technologies, and have achieved considerable success. However, the research on automatic modulation recognition technology has not yet matured and finalized, due to: One reason is that new modulation methods are constantly emerging, and the modulation types of communication signals are becoming more diverse, while previous modulation recognition algorithms only worked on specific types of modulation signals. Secondly, the complexity of wireless communication environments poses challenges to non cooperative communication. Compared to wired communication, wireless communication has its own characteristics: Firstly, the wireless channel of wireless communication is open and susceptible to interference from other signals and various noises; Second, radio propagation has a variety of ways, including diffraction, reflection and refraction. The signal received by the receiver will cause signal fading due to multi-path effects; Thirdly, there is also the Doppler effect in mobile communication, which can cause signal items to change at times. The multipath and Doppler effects seriously affect the reception quality of signals. In the process of non cooperative communication, the receiver cannot obtain the signal parameters of the sender like in cooperative communication. The diversified wireless communication technology requires non cooperative communication receiving systems to have characteristics such as wide coverage, strong adaptability, and anti fading. Thirdly, the signal environment is becoming increasingly dense, and at the same time, multiple signals with different modulation methods will enter the receiver. This puts forward new requirements for signal modulation recognition, that is, how to achieve recognition of multiple modulation signals at the same time. These situations all determine that there are many new research works to be carried out in the field of automatic modulation and recognition of communication signals [9].

This article briefly introduces a digital nonlinear phase modulation recognition algorithm proposed by E.E. Azzouz and A.K. Nandi to address these issues, because the features extracted by the nonlinear phase modulation recognition algorithm based on instantaneous features are all derived from the operation of instantaneous amplitude, instantaneous phase, and instantaneous frequency, the algorithm proposed by the author is used to identify, simulate, and analyze seven types of digital nonlinear phase modulation signals, and the decision process and selected decision threshold are provided.

3. Methods.

3.1. Classification of modulation methods .

From the perspective of modulation recognition, communication signals can be classified using various methods. The first classification is based on the information content contained in the signal, and any communication signal can be classified into one of the following four categories:

1. If a signal only contains amplitude information but not phase information, it is called an amplitude signal [10,11]. The so-called amplitude information here refers to the instantaneous amplitude of the signal not being constant; Phase information refers to the instantaneous phase of a signal that is not constant. Correspondingly, without amplitude information, the instantaneous amplitude of the signal is constant; No phase information refers to the instantaneous phase of a signal being constant. Amplitude signals such as MASK (M-scale amplitude keying) signals.
2. If a signal only contains phase information but not amplitude information, it is called a phase signal. For example, MFSK (M-ary Frequency Shift Keying) signal and MPSK (M-ary Phase Shift Keying) signal.
3. If a signal has both amplitude and phase information, it is called a composite signal. For example, MQAM (M-ary Orthogonal Amplitude Modulation) signal [12].
4. If a signal has neither amplitude nor phase information, it is called a carrier wave (CW) signal. Such as sine and cosine signals.

The second classification is based on the symmetry of the signal spectrum with respect to the carrier frequency. Usually, the spectrum of a signal consists of one carrier component and two sideband components, but in some modulation methods, the carrier component and two sideband components may not be all preserved. According to the presence of sidebands, communication signals can be divided into two categories: symmetric signals and asymmetric signals.

The third classification is divided into analog modulation signals and digital modulation signals based on the properties of modulation signals.

The fourth classification is divided into two categories based on the types of carriers: sine wave modulation and pulse modulation [13].

This project studies the sine wave modulation methods of digital signals, including the following modulation methods: 2ASK (binary amplitude keying), 4ASK (quaternary amplitude keying), 2FSK (binary frequency shift keying), 4FSK (quaternary frequency shift keying), 2PSK (binary phase shift keying), 4PSK (quaternary phase shift keying), and 16QAM (hexadecimal orthogonal amplitude modulation). Other modulation methods are not discussed here.

3.2. Recognition algorithm based on new instantaneous feature parameters . Parameter extraction and threshold selection: The author conducted nonlinear phase principle modulation recognition on 7 typical digital signals, including 2ASK, 4ASK, 2FSK, 4FSK, 2PSK, 4PSK, and 16QAM. After comprehensive consideration of various aspects, the following 5 instantaneous feature parameters were extracted for signal classification.

(1) The mean M_a^2 of the normalized instantaneous amplitude square at zero center. The mean M_a^2 of the normalized instantaneous amplitude square at zero center is obtained by the following equation:

$$M_a^2 = \frac{1}{N} \sum_{i=1}^{N_s} |a_{cn}(i)|^2 \tag{3.1}$$

In Equation 3.1, N_s is the total number of sampling points; $a_{cn}(i)$ is the zero center normalized instantaneous amplitude, and $a_{cn}(i)$ is calculated from Equation 3.2:

$$a_{cn}(i) = a_n(i) - 1 \tag{3.2}$$

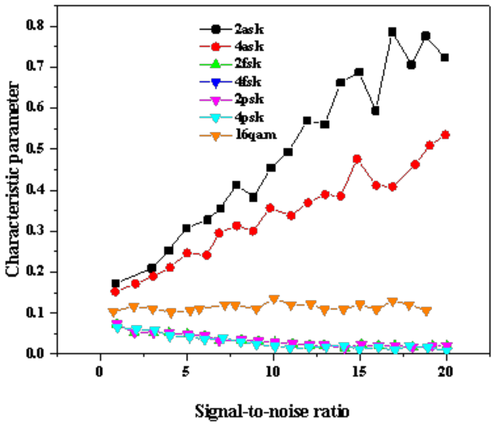

Fig. 3.1: The variation of parameter M_a^2 of modulated signals with different phase principles with signal-to-noise ratio

In Equation 3.2, the normalized instantaneous amplitude $a_n(i) = \frac{a(i)}{m_s}$, while $m_s = \frac{1}{N_s}\sum_{i=1}^{N_s} a(i)$ is the average of the instantaneous amplitude a (i), and the characteristic parameter M_a^2. Seven types of digital nonlinear phase modulation signals can be divided into three categories: MASK signals are classified into one category, 16QAM signals are classified into one category, and MFSK and MPSK signals are classified into another category. The instantaneous amplitude of MASK and 16QAM signals varies [14]; The instantaneous amplitude of the MPSK signal only undergoes a sudden change in amplitude at the moment of phase change, so its characteristic parameters are relatively small; The instantaneous amplitude of the MFSK signal is constant, the envelope is constant, and its characteristic parameter is zero. The actual simulation results are shown in Figure 1. From the figure, we can observe that at low signal-to-noise ratios, the characteristic parameters of signals modulated by different nonlinear phase principles are not significantly different due to the influence of noise[15]. However, as the signal-to-noise ratio increases, the characteristic parameters of signals modulated by different nonlinear phase principles begin to approach the theoretical calculated values, therefore, by selecting appropriate thresholds, MASK, 16QAM, and MFSK, MPSK signals can be separated. Based on multiple simulation attempts and weighing the impact on global decisions, the threshold $t1(M_a^2)$ of the mean M_a^2 of the normalized instantaneous amplitude squared at the zero center was selected as 0.12, and the threshold $t2(M_a^2)$ was selected as 0.08. When the threshold is $t2(M_a^2) < t(M_a^2) < t1(M_a^2)$, it is determined as a 16QAM signal; When the threshold is $t(M_a^2) > t1(M_a^2)$, it is judged as a MASK signal; When the threshold is $t(M_a^2) < t2(M_a^2)$, it is determined as an MFSK signal or an MPSK signal [16,17].

(2) Recursive Zero Center Normalized Instantaneous Amplitude Square Mean RM_a^2.

$$RM_a^2 = \frac{1}{N}\sum_{i=1}^{N_s} |ra_{cn}(i)|^2 \tag{3.3}$$

In Equation 3.3, N_s is the total number of sampling points, $ra_{cn}(i)$ is the recursive zero center normalization instantaneous amplitude, that is, after normalizing the zero center, the instantaneous amplitude $a_{cn}(i)$ is calculated, and then the zero center normalization instantaneous amplitude $ra_{cn}(i)$ is calculated by the following equation:

$$ra_{cn}(i) = \frac{a_{cn}(i)}{\frac{1}{N}\sum_{i=1}^{N_s} a_{cn}(i)} - 1 \tag{3.4}$$

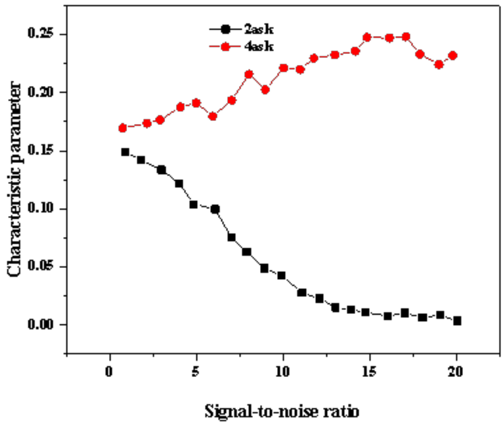

Fig. 3.2: Changes in parameter AA of modulated signals with different phase principles as a function of signal-to-noise ratio

The feature parameter RM_a^2 is used to distinguish between 2ASK signals and 4ASK signals. According to the time-domain characteristics of these two types of signals, their instantaneous amplitudes are 2 and 4, respectively, indicating that the RM_a^2 corresponding to the 4ASK signal is greater than the RM_a^2 corresponding to the 2ASK signal. Therefore, by setting an appropriate threshold value $t(RM_a^2)$, 2ASK and 4ASK signals can be identified. Based on multiple simulation attempts and weighing the impact on global decisions, finally, the threshold $t(RM_a^2)$ of the mean RM_a^2 of the normalized instantaneous amplitude square of the zero center is selected as 0.17. The variation of the mean RM_a^2 of the recursive zero center normalized instantaneous amplitude square of modulated signals with different digital nonlinear phase principles with signal-to-noise ratio is shown in Figure 3.2.

(3) The mean M_f^2 of the square of the normalized instantaneous frequency at zero center.

$$M_f^2 = \frac{1}{N_s} \sum_{i=1}^{N_s} |f_{cn}(i)|^2 \tag{3.5}$$

In Equation 3.5, N_s is the total number of sampling points: $f_{cn}(i)$ is the zero center normalized instantaneous frequency. According to the time-domain characteristics of the signal, the MFSK signal has at least 2 instantaneous frequency values, while the MPSK signal only has 1 instantaneous frequency value, meaning that the M_f^2 corresponding to the MFSK signal is greater than the M_f^2 corresponding to the MPSK signal. Therefore, this feature parameter can be used to distinguish between MFSK signals and MPSK signals. Based on multiple simulation attempts and weighing the impact on global decisions, finally, the threshold $t(M_f^2)$ of the mean M_f^2 of the zero center normalized instantaneous frequency squared is selected as 0.075. The variation of the mean M_f^2 of the zero center normalized instantaneous frequency square of modulated signals with different digital nonlinear phase principles with signal-to-noise ratio is shown in Figure 3.3 [18].

(4) Recursive Zero Center Normalized Instantaneous Frequency Square Mean. RM_f^2

$$RM_f^2 = \frac{1}{N_s} |rf_{cn}(i)|^2 \tag{3.6}$$

In Equation 3.6, N_s is the number of sampling points, and $rf_{cn}(i)$ is the recursive zero center normalized instantaneous frequency, namely, normalize the instantaneous frequency of the zero center and then calculate

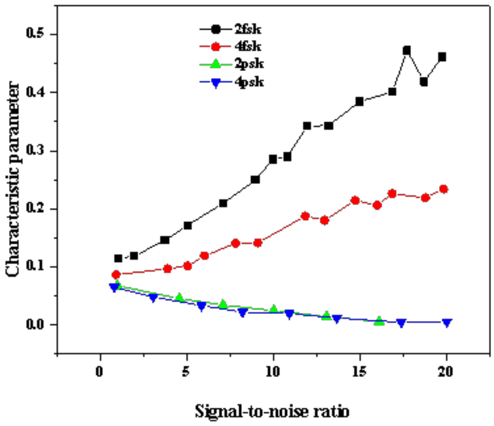

Fig. 3.3: The variation of parameter M_f^2 of modulated signals with different phase principles with signal-to-noise ratio

the normalized instantaneous frequency $f_{cn}(i)$ of the zero center using the following formula:

$$f_{cn}(i) = \frac{f_{cn}(i)}{\frac{1}{N_s}\sum_{i=1}^{N_s} f_{cn}(i)} - 1 \tag{3.7}$$

In Equation 3.7, $f_{cn}(i)$ is the zero center normalized instantaneous frequency. According to the time-domain characteristics, the number of instantaneous frequency values of the 2FSK signal is 2, which is significantly smaller than the number of instantaneous frequency values of the 4FSK signal, therefore, the RM_f^2 value corresponding to 2FSK is smaller than the RM_f^2 value of 4FSK, so this feature parameter RM_f^2 can distinguish between 2FSK and 4FSK signals. Based on multiple simulation attempts and weighing the impact on global decisions, the threshold $t(RM_f^2)$ of the mean RM_f^2 of the normalized instantaneous frequency square of the recursive zero center was ultimately selected as 0.225 [19]. The variation of the mean RM_f^2 of the recursive zero center normalized instantaneous frequency square of modulated signals with different digital nonlinear phase principles with signal-to-noise ratio is shown in Figure 3.4.

(5) Mean M_p^2 of normalized instantaneous phase squared at zero center.

$$M_p^2 = \frac{1}{N}\sum_{i=1}^{N_s} |p_{cn}(i)|^2 \tag{3.8}$$

In Equation 3.8, N_s is the number of sampling points, $p_{cn}(i)$ is the zero center normalized instantaneous phase, calculated by the following equation:

$$p_{cn}(i) = p_n(i) - 1 \tag{3.9}$$

In Equation 3.9, $p_n(i) = \frac{p(i)}{m_s}$, while $m_s = \frac{1}{N_s}\sum_{i=1}^{N_s} p(i)$ is the average of the instantaneous phase p (i). The instantaneous phase number of 4PSK is greater than that of 2PSK, and the characteristic parameter M_p^2 can distinguish between 4PSK and 2PSK signals. Based on multiple simulation attempts and weighing the impact on global decisions, the threshold $t(M_p^2)$ of the mean M_p^2 of the normalized instantaneous amplitude squared at the zero center was ultimately selected as 0.2. The variation of the mean M_p^2 of the zero center normalized instantaneous phase square of modulated signals with different digital nonlinear phase principles with signal-to-noise ratio is shown in Figure 3.5.

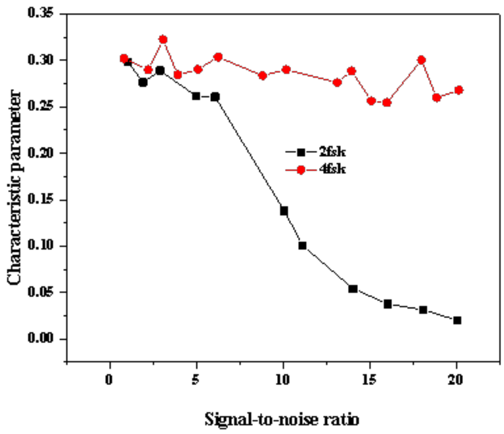

Fig. 3.4: The variation of parameter RM_f^2 of modulated signals with different phase principles with signal-to-noise ratio

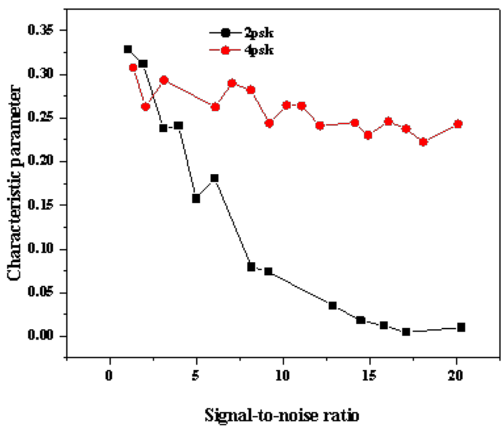

Fig. 3.5: The variation of parameter M_p^2 of modulated signals with different phase principles as a function of signal-to-noise ratio

4. Results and Analysis. Figure 4.1 is the non-linear phase principle modulation recognition flowchart of the algorithm in this paper. In the recognition algorithm proposed by the author, only 5 feature parameters can identify 7 types of digital nonlinear phase principle modulation signals. However, the five features proposed by scholars E.E. Azzouz and A.K. Nandi can only recognize six types of digital nonlinear phase modulation signals [20,21].

Firstly, in order to ensure that when the signal sender uses symbol 0 to modulate the MASK signal using the nonlinear phase principle, the MASK can be recognized, we can only use the feature M_a^2 related to instantaneous amplitude to distinguish MASK signals from other signals, and RM_a^2 to distinguish 2ASK signals from 4ASK signals.

Secondly, from the instantaneous characteristic maps of MFSK and MPSK, it can be seen that the instantaneous frequency of MFSK has only a finite number of discrete values, while the instantaneous frequency of

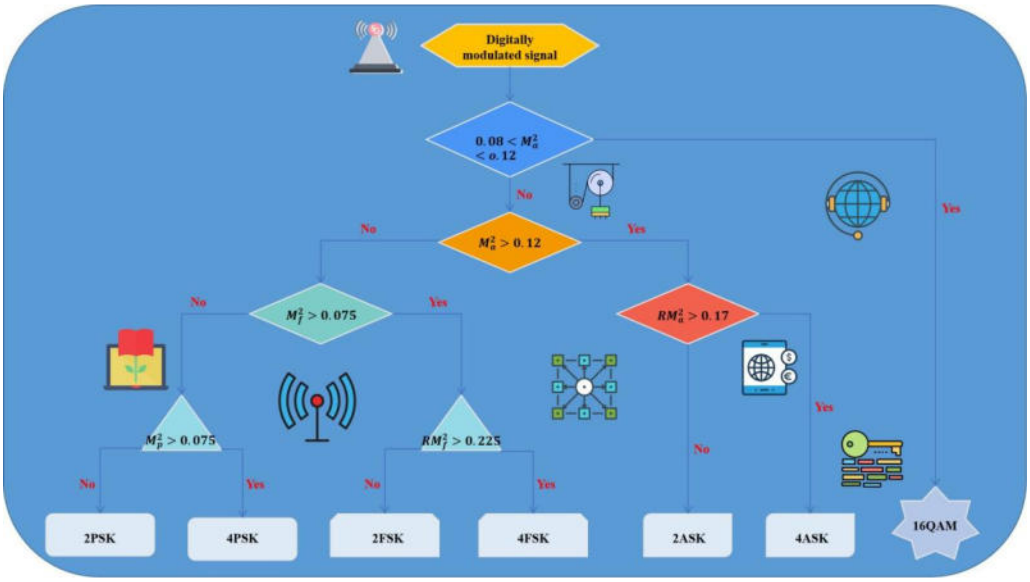

Fig. 4.1: Nonlinear Phase Principle Modulation Recognition Flowchart of the Author's Algorithm

MPSK is constant, the use of feature M_f^2 can effectively distinguish between MFSK signals and MPSK signals. It is not appropriate to use feature M_p^2 to distinguish between MFSK signals and MPSK signals, because the instantaneous phase of the MFSK signal is not constant, but time-varying.

Finally, feature RM_f^2 is used to distinguish between 2FSK and 4FSK signals, and feature M_p^2 is used to distinguish between 2PSK and 4PSK signals. At this point, all seven types of digital nonlinear phase modulation signals have been distinguished [22].

Figure 4.2 shows the recognition results of seven digital nonlinear phase modulation signals using the author's algorithm under different signal-to-noise ratios. As can be seen from Figure 4.2, when the signal-to-noise ratio is greater than or equal to 10dB, the recognition accuracy of all seven digital nonlinear phase modulation signals can reach 100%.

E. Azzouz and A.K. Nandi, two scholars, did not provide a simulation diagram similar to Figure 4.2 showing the variation of digital nonlinear phase principle modulation signal recognition results with signal-to-noise ratio. Instead, they only provided the recognition accuracy under three conditions of signal-to-noise ratio: 10dB, 15dB, and 20dB[23]. Table 1 is a comparison table of the correct recognition rates of the author's algorithm and classical algorithm under three different signal-to-noise ratios of 10dB, 15dB, and 20dB, respectively. By comparison, it can be seen that, compared with the classic algorithms of E.E. Azzouz and A.K. Nandi, the new algorithm proposed by the author achieves better recognition results at low signal-to-noise ratios by adding a 16QAM nonlinear phase principle modulation method .

5. Conclusion. The features extracted by the nonlinear phase modulation recognition algorithm based on instantaneous information are all derived from the operation of instantaneous amplitude, instantaneous phase, and instantaneous frequency, the author analyzed how to extract these three instantaneous feature parameters. Simulation and analysis were conducted on the recognition of seven types of digital nonlinear phase modulation signals using the feature parameters proposed by the author, the decision process and selected decision threshold were provided, and the results showed that the author's algorithm improved the recognition success rate. In recent years, the research methods and directions of automatic nonlinear phase modulation recognition algorithms have been continuously expanded, and progress has been made to some extent, however, there are still many key issues that have not been well resolved. The author's research on nonlinear phase principle modulation recognition algorithms still has many shortcomings. All research on nonlinear phase principle modulation recognition focuses on certain types of modulation signals, the author only studied seven

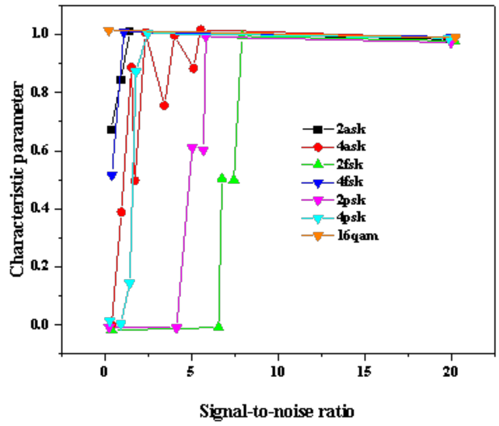

Fig. 4.2: Recognition results of seven types of digital nonlinear phase modulation signals under different signal-to-noise ratios

Table 4.1: Comparison of the correct recognition rates of the author's algorithm and classical algorithm under different signal-to-noise ratios

modulation	Author's Algorithm			Assical algorithm		
	SNR=10	SNR=15	SNR=20	SNR=10	SNR=15	SNR=20
2ASK	100%	100%	100%	98.39%	98.3%	100%
4ASK	100%	100%	100%	100%	99.8%	100%
2FSK	100%	100%	100%	99.5%	99.5%	100%
4FSK	100%	100%	100%	98.3%	98.5%	100%
2PSK	100%	100%	100%	99.3%	99.3%	99.3%
4PSK	100%	100%	100%	98.8%	98.8%	99.8%
16QAM	100%	100%	100%	-	-	-

commonly used digital modulation signals and did not involve other types of digital modulation signals or analog modulation signals. With the continuous emergence of new modulation methods, it is necessary to study automatic recognition algorithms suitable for a wider range of modulation signals.

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