Algorithms for Modulation Recognition of Narrowband Power Line Carrier Communication Signals

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Abstract. Automatic identification of modulated signals is an important technology of power line communication. Aiming at the problems of low signal recognition rate and characteristic parameter extraction in power line communication channel, this paper uses amplitude variance value of wavelet transform and higher order cumulant as the identification parameter, and designs a signal recognizer based on improved support vector machine. Under the condition of power line channel environment, the recognizer of this paper is less than the existing recognition method in computational complexity, and has good robustness to power line noise. At the same time, it avoids the shortcomings of traditional neural network such as under-learning and over-learning. The simulation results show that when the SNR is 5 dB, power line communication signals through the recognizer, which the correct identification rate can reach 91%.

1. Introduction

Power line communication is divided into narrowband communication (NB-PLC, 3–500 kHz) and broadband communication (BB-PLC, 1.8–250 MHz). Narrowband communication is widely used in smart meters. The broadband communication is used in home power grids, and it can provide hundreds of Mb/s high-speed data transmission. The Telecommunications Industry Association-1113 and the International Telecommunication Union (ITU-T) have formulated some standards for power line communication, such as IEEE P1901, ITU-TG.hn[1].

The identification of power line carrier communication signals has become a research direction in this field. Because the power line channel has strong noise interference, attenuation and multipath effects[1], it is very difficult to obtain an ideal modulated signal at the receiving end. Therefore, the recognition of modulated signals has become a problem that must be solved in power line communication.

There are two main types of signal modulation pattern recognition algorithms: recognition methods based on statistical patterns[2] and recognition methods based on detection theory[3]. Due to the computational complexity of the detection theory method, fewer types of recognition signals, and the likelihood function of the signal can only be obtained in the Gaussian white noise environment, this method is not suitable for power line channels. At present, the main research direction of modulation recognition algorithms is to combine statistical recognition methods with neural network methods, which can achieve better recognition results under the premise of selecting reasonable eigenvalues and neural network algorithms.

In the research of automatic identification of digital signals, Nandi and Azzouz have made great
contributions[2][4]. They successfully identified 2ASK, 4ASK, 2PSK, 4PSK, 2FSK, 4FSK signals using decision theory methods and neural network methods. Diego Alves Amoedo[5] used the support vector machine method to successfully identify AM, FM, BPSK, QPSK, 16QAM, 64QAM and GMSK signals, but the recognition effect is not very satisfactory. Husam Alzaq[6] used neural network methods to successfully identify MASK, MPSK, and MFSK signals, but the neural network has over-learning and under-learning, which will have a certain impact on the recognition effect. Salman Hassanpour[7] used the wavelet transform method to successfully identify DPSK, PSK and MSK; Alharbi Hazza[8] proposed a feature-based method to successfully identify FSK, ASK, PSK, QAM and other signals, but the identification device designed Complicated calculations. Liedtke[9] successfully identified AM, 2ASK, 2PSK, 4PSK, and 2FSK signals using statistical patterns and decision theory methods, but the implementation of this recognizer is more complicated, and error-free recognition can only be achieved when the signal-to-noise ratio is greater than 18dB. Literature[10][11] uses wavelet features as the feature elements of support vector machines to identify signals. Literature[12] uses the high-order statistical matrix of continuous wavelet transform as the feature set, and uses the forward neural network as the recognizer. Its purpose is to distinguish different multi-shift keying signals.

Most of the methods used in the above documents complete the signal identification under the condition of Gaussian white noise, and this article takes into account the actual situation of the PLC channel, and it is reflected in the recognition rate and the type of identification signal. In the aspect of PLC signal recognition, this paper adopts the statistical pattern recognition method, and designs an improved modulated signal recognizer based on support vector machine. First of all, to obtain the high-order cumulant of the signal, and then perform wavelet transform processing on it, and extract the characteristic parameters. The two types of characteristic parameters are input into the improved support vector machine to finally identify the signal type. In the approximate power line channel environment, the simulation results show that the method can get better results.

2. Signal and Channel Model

2.1. Signal Model
After the modulated signal passes through the power line communication channel, assuming that the carrier of the received signal is complete and the frequency and phase are synchronized, the baseband expression of the modulated signal can be defined as[13]:

$$S(t) = \sum_{k} \sqrt{E} h_k p_k(t-kT_s) \exp[j(2\pi f_c t + \theta)] + n(t) \quad (1)$$

where \( k = 1, 2, \ldots, N \), \( N \) is the length of the transmitted symbol sequence, \( h_k \) is the transmitted symbol sequence, \( p(t) \) is the waveform of the transmitted symbol, \( T_s \) is the symbol width, \( E \) is the signal energy, \( f_c \) is the carrier frequency, \( \theta \) is the carrier phase, \( n(t) \) is the power line channel noise[14][15].

According to the characteristics of the modulated signal, after frequency down conversion, the expressions of MASK, MPSK, MFSK, and MQAM are represented by formulas (2), (3), (4) and (5) respectively[16].

$$S(t) = \sum_{k} \sqrt{E} a_k p_k(t-kT_s) \exp[j(2\pi f_c t + \theta)] + n(t) \quad (2)$$

where \( a_k \in \{2m-1-M \mid m = 1, 2, \ldots, M \} \).

$$S(t) = \sum_{k} \sqrt{E} \exp(j2\pi f_c t) p_k(t-kT_s) \exp[j(2\pi f_c t + \theta)] + n(t) \quad (3)$$

where \( f_k \in \{(2m-1-M)\Delta f \mid m = 1, 2, \ldots, M \} \), \( \Delta f \) is the frequency offset.
\[ S(t) = \sum_k \sqrt{E} \exp(j\varphi_k)(t-kT_s)\exp[j(2\pi f_s t + \vartheta)] + n(t) \] (4)

where \( \varphi_k \in \{2\pi(m-1)/M, m = 1, 2, \cdots, M \} \).

\[ S(t) = \sum_k \sqrt{E}(a_k + b_k)(t-kT_s)\exp[j(2\pi f_s t + \vartheta)] + n(t) \] (5)

where \( a_k, b_k \in \{2m-1-\sqrt{M} \mid m = 1, 2, \cdots, \sqrt{M} \} \).

2.2. Channel Model

2.2.1. Background Noise Model. The actual power line noise includes two parts: background noise and impulse noise\[14][17]. The background noise in this paper is represented by a model in which the probability density obeys the Nakagami-\(m\) distribution\[15][18][19]. Literature\[20\] verifies that the noise model is feasible. The feature vector\((X)\) of background noise obeys the Nakagami-\(m\) distribution, and its probability density function is:

\[ f(x) = \frac{2(m)^m x^{2m-1}}{\Gamma(m)} \exp(-\frac{mx^2}{\Omega}); x \geq 0 \] (6)

where \( \Gamma(*) \) is the gamma function, \( \Omega \) is the average power of the background noise, defined as \( \Omega = E[X^2] \), \( E[*] \) is the expectation, \( m \) is the parameter of Nakagami-\(m\), that is, the shape factor, which represents the severity of attenuation. \( m = E[X^2]/E[(X^2 - E[X^2])^2] \geq 0.5 \).

2.2.2. Impulse Noise Model. Under the action of the unit impulse function \( \text{imp}(t) \), the impulse noise model under the power line channel can be obtained \(n_{\text{imp}}\):

\[ n_{\text{imp}}(t) = \sum_{i=1}^{N} A_i \cdot \text{imp}(\frac{t-t_{\text{arr},i}}{t_{\text{win},i}}) \] (7)

The parameter \( A_i \) represents the amplitude of the \(i\)-th impulse noise, \( t_{\text{win},i} \) represents the duration of the \(i\)-th noise, that is, the width of the noise, and \( t_{\text{arr},i} \) represents the time when the \(i\)-th noise is generated. The values of \( A_i, t_{\text{win},i} \) and \( t_{\text{arr},i} \) are random, and the specific values can be found in literature\[21\].

3. Feature Extraction

3.1. Calculation of Higher-Order Cumulants

Assuming that the \(k\)-order real stationary random process \( x(t) \) has zero mean, its \(k\)-order cumulant calculation formula is\[22\]:

\[ C_{ki}(\tau_1, \tau_2, \cdots, \tau_{k-1}) = \text{cum}(x(t), x(t+\tau_1), \cdots, x(t+\tau_{k-1})) \] (8)

The received signal can be expressed as \( r(t) = s(t) + n(t) \), \( s(t) \) represents the transmitted signal, \( n(t) \) represents the power line channel noise, that is background noise, random impulse noise, and \( s(t) \) and \( n(t) \) are independent. According to the characteristics of the cumulant, the following equation can be obtained:

\[ \text{cum}(r) = \text{cum}(s) + \text{cum}(n) \] (9)

Before the high-order cumulant processing of the received signal, the wavelet denoising method is used to process the signal, which can remove part of the background noise and impulse noise. Then
through the calculation of the high-order cumulant, the approximate equation of (9) is obtained[23]:
\[
\text{cum}(r) \approx \text{cum}(s)
\]
(10)

From equation (10), under the influence of power line noise, calculating the high-order cumulant value of the signal can also identify the signal modulation mode. In an ideal channel, if the transmitted symbols are independent and identically distributed, and the energy of the signal is \( E \), the theoretical value of each cumulant is shown in Table 1.

| signal type | \( c_{-2} \) | \( c_{-1} \) | \( c_{0} \) | \( c_{1} \) | \( c_{2} \) | \( c_{3} \) |
|-------------|--------------|--------------|--------------|--------------|--------------|--------------|
| 2ASK        | \( E \)      | \( E \)      | \( 2E^i \)   | \( 2E^i \)   | \( 16E^i \)  | \( 16E^i \)  |
| 4ASK        | \( E \)      | \( 1.36E^i \)| \( 1.36E^i \)| \( 1.36E^i \)| \( 8.32E^i \)| \( 8.32E^i \)|
| 8ASK        | \( E \)      | \( 1.15E^i \)| \( 1.15E^i \)| \( 1.15E^i \)| \( 6.9E^i \)  | \( 6.9E^i \)  |
| 2FSK        | 0            | \( E \)      | 0            | \( E^i \)    | 0            | \( E^i \)    |
| 4FSK        | 0            | \( E \)      | 0            | \( E^i \)    | 0            | \( E^i \)    |
| 8FSK        | 0            | \( E \)      | 0            | \( E^i \)    | 0            | \( E^i \)    |
| 2PSK        | \( E \)      | \( 2E^i \)   | \( 2E^i \)   | \( 2E^i \)   | \( 16E^i \)  | \( 16E^i \)  |
| 4PSK        | 0            | \( E^i \)    | 0            | \( E^i \)    | 0            | \( 4E^i \)   |
| 8PSK        | 0            | \( E \)      | 0            | \( E^i \)    | 0            | \( 4E^i \)   |
| 16QAM       | 0            | \( 0.68E^i \)| 0            | \( 0.68E^i \)| 0            | \( 2.08E^i \) |

3.2. Feature Parameter Extraction

Table 1 shows the high-order cumulant values of some signals. However, 2ASK and 2PSK signals and MFSK and 8PSK signals cannot be identified using the cumulant method. Through literature [24], it is known that the MFSK signal has amplitude modulation characteristics after derivation. Therefore, calculating the high-order cumulant of the derivative of the MFSK signal can identify the MFSK signal[24].

\[
r'(t) = \sqrt{E} \sum_n \{ \exp[j(2\pi f_c t + \theta_c)]\delta(t - kT_s) + j2\pi f_c \exp[j(2\pi f_c t + \theta_c + \pi/2)]p(t - kT_s)\} + n'(t)
\]
(11)

In order to eliminate the impact of the impact function, the median filter processing of (11) is obtained:

\[
r''(t) = \sqrt{E} \sum_n j2\pi f_c \exp[-j(2\pi f_c t + \theta_c + \pi/2)]p(t - kT_s) + n''(t)
\]
(12)

After derivation and median filtering, \( n''(t) \) is still the power line channel noise. The Haar wavelet denoising process is performed on equation (12), and then the cumulative value of the second derivative of the MFSK signal is given in Table 2.

| signal type | \( c_{20} \) | \( c_{21} \) | \( c_{40} \) | \( c_{41} \) | \( c_{42} \) | \( c_{60} \) |
|-------------|--------------|--------------|--------------|--------------|--------------|--------------|
| 2FSK        | 0            | \( E\Delta\omega^i \) | 0            | 0            | \( -E^2\Delta\omega^i \) | 0            |
| 4FSK        | 0            | \( 5E\Delta\omega^i \) | 0            | 0            | \( -9E^2\Delta\omega^i \) | 0            |
| 8FSK        | 0            | \( 21E\Delta\omega^i \) | 0            | 0            | \( -105E^2\Delta\omega^i \) | 0            |

According to Table 1 and Table 2, this paper designs a signal recognition characteristic parameter with better anti-noise performance, and its specific representation is as follows:
where, \( f_1, f_2, f_3 \) and \( f_4 \) are the characteristic values calculated according to the results of Table 1, and are the characteristic values of the MFSK signal obtained according to the results of Table 2. The calculated characteristic parameters are shown in Table 3.

Table 3. The value of characteristic parameter.

|         | 2ASK/2PSK | 4ASK | 8ASK | 2FSK | 4FSK | 8FSK | 4PSK | 8PSK | 16QAM |
|---------|-----------|------|------|------|------|------|------|------|-------|
| \( f_1 \) | 1         | 1    | 1    | ---  | ---  | ---  | 1    | ---  | 1     |
| \( f_2 \) | 0.5       | 0.73 | 0.869| ---  | ---  | ---  | 0    | ---  | 0     |
| \( f_3 \) | ---       | ---  | 1    | 1    | 1    | 16   | 16   | 17.7 | 13.7  |
| \( f_4 \) | 16        | 8.32 | 6.9  | ---  | ---  | ---  | ---  | ---  | ---   |
| \( f_5 \) | ---       | ---  | 1    | 2.78 | 4.20 | ---  | ---  | ---  | ---   |

The method described by equation (13) still cannot identify 2ASK and 2PSK signals. According to the literature[25], the wavelet transform amplitude variance of 2ASK and 2FSK signals has obvious differences, so this paper performs Haar wavelet transform on these two signals, and then calculates the amplitude variance[25]. So as to determine the size of the decision threshold. These two signals can be directly judged based on the support vector machine, which reduces the complexity of recognition. The simulation results of the amplitude variance of 2ASK and 2FSK signals are shown in Figure 2(g).

4. Recognizer Design

SVM can realize the recognition of two types of signals, but when it is necessary to recognize multiple signals, the extended SVM[26][27] should be used. Literature[27] uses the 1-VS-R (One-vs-Rest) SVM classification algorithm, and its structural logic is relatively simple. For m-type signals, m support vector machines are required, but each support vector machine needs to use all Samples are used for training; Literature[28] uses the Decision Directed Acyclic Graph (DDAG) SVM classification algorithm, which is relatively simple in training support vector machines. Except for the top support vector machine, each other only Part of the sample is used for training, but the logic is more complicated, and the number of support vector machines is also large[28]. In this paper, combining the characteristics of the required characteristic parameters, a support vector machine with a binary tree structure is used to identify the signal. Because the judgment logic of the binary tree structure is relatively simple, there are fewer support vector machines used, and the training samples are gradually decreasing[28]. The structure of the classifier used in this paper is shown in Figure 1, where the feature parameters represent a support vector machine, and the decision threshold can directly identify the signal, so no support vector machine is needed. The specific identification steps of the recognizer in this article are as follows:

1) Use wavelet transform to denoise the received signal;
2) Calculate the high-order cumulant of the signal and the amplitude variance of the wavelet transform of 2ASK and 2FSK signals, and construct characteristic parameters;
3) Use the extracted feature parameters to form feature vectors as the input of the BT-SVM classifier;
4) Choosing the kernel function for SVM, the radial kernel function is selected in the identification experiment of this paper. The radial kernel function can plan the samples non-linearly into a higher-dimensional space, thereby solving the problem of the non-linear relationship between class labels and attributes[29].
5) Train the BT-SVM classifier, and classify and identify the test samples after completing the training.
In the designed classifier, the experimental simulation of the feature parameter $f_1$–$f_5$ and the wavelet amplitude variance used by the support vector machine is shown in Figure 2. The specific classification situation is described in Figure 1.

![Figure 1. Flowchart for recognition of digital modulation.](image)

(a) the simulation curve of $f_1$  
(b) the simulation curve of $f_2$  
(c) the simulation curve of $f_3$  
(d) the simulation curve of $f_4$  
(e) the simulation curve of $f_4$  
(f) the simulation curve of $f_5$
As shown in Figure 2, the feature parameter $f_1$ in Figure 2(a) is used to identify {2ASK, 2PSK, 4ASK, 8ASK, 4PSK and 16QAM} and {2FSK, 4FSK, 8FSK and 8PSK}. The simulation curve in Figure 2(b) is used identify {2ASK, 2PSK, 4ASK and 8ASK} and {4PSK and 16QAM}. The simulation curve in Figure 2(c) can be 4PSK and 16QAM; the simulation curve in Figure 2(d) can identify {2FSK, 4FSK, 8FSK} and 8PSK. The feature parameter $f_4$ is used to identify 2ASK/2PSK, 4ASK and 8ASK in Figure 2(e). The feature parameter $f_5$ in Figure (f) can identify 2FSK, 4FSK and 8FSK. The feature parameter $f_6$ in Figure 2(g) can identify 2ASK and 2PSK.

Under the structure of the recognizer shown in Figure 1, Tables 4 and 5 show the correct recognition rate of each modulated signal. The result in the table is an average value obtained after 600 independent experiments.

### Table 4. The modulation mode recognition correct rate at SNR=17 dB (%).

| Modulated signal at sender | Receiver modulated signal |
|----------------------------|---------------------------|
|                            | 2ASK/2PSK | 4ASK | 8ASK | 4PSK | 8PSK | 16QAM |
| 2ASK/2PSK                  | 97.5      | 2.5  | 0    | 0    | 0    | 0     |
| 4ASK                       | 2.1       | 97.9 | 0    | 0    | 0    | 0     |
| 8ASK                       | 0         | 5.2  | 94.8 | 0    | 0    | 0     |
| 4PSK                       | 0         | 0    | 93.2 | 6.8  | 0    | 0     |
| 8PSK                       | 0         | 0    | 5.3  | 94.7 | 0    | 0     |
| 16QAM                      | 0         | 0    | 0    | 0    | 0    | 100   |

### Table 5. The modulation mode recognition correct rate at SNR=17 dB (%).

| Modulated signal at sender | Receiver modulated signal |
|----------------------------|---------------------------|
|                            | 2FSK | 4FSK | 8FSK |
| 2FSK                       | 100  | ---  | 0    |
| 4FSK                       | 4.5  | 93.2 | 2.2  |
| 8FSK                       | 0    | 1.6  | 98.4 |

5. Simulation and Experimental Analysis

The frequency range of narrowband power line carrier in my country is 40~500KHZ, and the bandwidth of carrier frequency band is 4KHZ. The simulation parameters are set as follows: sampling frequency $f_s$ is 600KHz, carrier frequency $f_c$ is 60KHz, bit rate $R_s$ is 1200bps, frequency offset is 2KHz,
number of symbols is 600, carrier amplitude is 1, and signal-to-noise ratio ranges from -5dB to 20dB. The noise is the power line channel noise. Each signal was subjected to 600 independent experiments, and there was no correlation between the signals. The feature parameters are extracted by formula (13), 400 experimental results are used as training samples, and the others are used as test samples. When the signal-to-noise ratio is -5dB~20dB, the simulation data of each signal characteristic parameter is shown in Figure 2. It can be seen from Figure 2 that the method used in this article has a good recognition effect and also has a good anti-noise performance.

In order to illustrate the effectiveness of the recognizer in this paper, under the same Gaussian white noise condition, the recognizer in this paper is compared with similar recognizers[29], as shown in Figure 3. When the signal-to-noise ratio is -2dB, the recognition rate of the recognizer designed in [29] is 82%, and the recognition rate of the recognizer designed in this paper can reach 87.1%. As the signal-to-noise ratio increases, although the recognition rates of the two algorithms have no obvious difference, the recognition device in this paper can recognize more kinds of signals, and the training samples are gradually reduced, reducing the complexity of the operation.

In addition, this paper uses BT-SVM classifier and forward neural network classifier to analyze the recognition performance of power line modulation signals. When the signal-to-noise ratio is between -5dB and 20dB, Figure 4 shows the simulation curves of the recognition rates of the two classifiers. It can be seen that under the small signal-to-noise ratio, the improved support vector machine recognizer and the forward neural network recognizer have good anti-noise performance, but in the case of large signal-to-noise ratio, due to the forward neural network, there are shortcomings of under-learning and over-learning, so the forward neural network recognizer cannot achieve good recognition results.

6. Conclusion
This paper proposes an improved binary tree-based support vector machine modulation signal recognition method for the power line channel environment. Extracting six feature parameters can distinguish 2ASK, 4ASK, 8ASK, 2FSK, 4FSK, 8FSK, 2PSK, 4PSK, 8PSK and 16QAM signals. The recognition algorithm of this recognizer is relatively simple. The high-order cumulant of the power line signal is used as the characteristic parameter of signal identification, and the decision threshold of the amplitude variance of 2ASK and 2FSK signals is given. In this way, in the support vector machine classifier with the binary tree structure, the selection of the decision threshold is avoided, and the number of support vector machines is also reduced. Moreover, the recognizer has good robustness to power line noise. In order to verify the performance of the proposed recognition, this paper has done a lot of simulation experiments and comparison experiments. The simulation results show that when the signal-to-noise ratio is 5dB, the recognition rate of the forward neural network classifier is 81%, while the recognition rate of the recognizer proposed in this paper can reach 91%. This effect is achieved because both high-order cumulants and wavelet transform amplitude variance have good anti-noise performance when extracting feature parameters. As the number of support vector machines is reduced, the computational complexity of the algorithm is also reduced accordingly.

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