Automatic Modulation Recognition of Communication Signals

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Abstract

Modulation identification of communication signals is an important content of the electronic countermeasure procedure and a hot topic in the research field of signal processing. Generally speaking, the essential problem of communication signals' recognition is a pattern recognition problem. In these paper, Firstly, the feasibility of the improved method to distinguish between analog modulation signals and digital modulation signals based on Haar Wavelet Transform(HWT) is demonstrated. Secondly, a identification method of analog modulation signals based on the higher order moment of envelope and the spectrum symmetry is presented. Thirdly, an identification method of digital modulation signals using high-order cumulants is suggested. Finally, an experiments is designed to prove the validity of the research theory. The final result shows that the recognition method in this paper has a well prospect in communication signals' recognition.

Keywords: Communication signal's recognition; Wavelet transform; higher-order moment of envelope; High-order cumulants;

1. Introduction

There are so many communication signals all available with different types of modulation and different frequencies. It is necessary to identify and closely monitor these signals for few applications. In military, there are many applications such as surveillance, electronic warfare and threat analysis. One of the important characteristics is the signal modulation type which describes how the information is being carried in the signal. In civilian, there are many applications such as signal confirmation, interference identification, monitoring and spectrum management.

In this paper, the modulation recognition of the signals include AM, FM, DSB, LSB, USB, 2ASK/BPSK, 4ASK, QPSK, 8PSK, 16QAM, 32QAM are researched, Firstly, as an effective symbol rate estimation method, wavelet transform theory has been widely used method in distinguishing between analog modulation signals and digital modulation signals[1-3] and a improved method has been proposed to solve some problems in common methods. Secondly, after the signal prior information whether it is analog modulation or digital modulation is acquired, the higher order moment of envelope J and the spectrum symmetry P can be used to identify the analog modulation signals[4-5] and the high-order cumulants theory can be used to identify the digital modulation signals[6-8]. In the last section of the paper, the effectiveness of the approach is proved by a scientific experiment based on MATLAB software.

2. Proposed Modulation Recognition Procedure

2.1. Communication Signals Model

The waveform of analog modulation signals with noise pollution can be expressed as

$$r(t) = m(t) \cos[2\pi f_c t + \phi(t) + \theta] + n(t) \quad (0-1)$$

And the digital modulation signals with noise pollution can be expressed as

$$r(t) = \sum_k a_k \sqrt{E} p(t - kT_s) \exp(j2\pi f_c t + j\theta_c) + n(t), k = 1, 2, \dots, N \quad (0-2)$$

Among them, $m(t)$ is the amplitude of the signal, f_c is the carrier frequency, $\phi(t)$ is the modulated phase, θ is the initial phase, N is the length of element sending sequence, a_k is the sequence of transmitting symbol, E is the symbol energy of transmitting codes, $p(t)$ is the waveform of transmitting symbols, T_s is the code width, θ_c is the carrier phase, $n(t)$ is Gaussian white noise with zero mean, and the signals and noise $n(t)$ are independent. Suppose carrier frequency, phase and timing are all synchronized, after the conversion, the digital modulation signals can be expressed as

$$r(t) = \sum_k \sqrt{E} a_k p(t - kT_s) \exp(j\theta_c) + n(t) \quad (0-3)$$

2.2. Recognition between Analog Modulation Signals and Digital Modulation Signals

K.C.Ho first proposed a method based on wavelet transform to estimate the symbol rate[1]. This is a linear transformation method. In order to properly characterize the characteristics when the code of digital communication signal is switching, Haar wavelet was used as the mother wavelet function. QAM, PSK and FSK signals in analytical form of intermediate frequency can be expressed as:

$$s(k) = \begin{cases} \sqrt{s_i} e^{j(\phi_i + \omega_i k)} e^{j(\omega_c k + \theta_c)} & (i-1)T \leq k \leq iT \\ \sqrt{s_{i+1}} e^{j(\phi_{i+1} + \omega_{i+1} k)} e^{j(\omega_c k + \theta_c)} & iT \leq k \leq (i+1)T \end{cases} \quad (0-4)$$

Here, $\sqrt{s_i}$, ϕ_i and ω_i are respectively the information of amplitude, phase and frequency, ω_c and θ_c are respectively the frequency and initial phase of the carrier wave after the signal was shifted to intermediate frequency. The amplitude of PSK and FSK signals remain unchanged, only the frequency of FSK signals will change, and the phase of QAM and PSK signals will change in the code switching.

If the wavelet transform integral interval is in a code period, the steady-state value of WT can be gotten as follow:

$$|WT_s(a, n)| = 2\sqrt{\frac{1}{a}} \left| \frac{\sin^2[(\omega_c + \omega_i)a/4]}{\sin[(\omega_c + \omega_i)/2]} \right|, (i-1)T + \frac{a}{2} \leq n \leq iT - \frac{a}{2} \quad (0-5)$$

If the integral interval spans across two code periods, the value of WT when $n = iT$ can be gotten as follow:

$$|WT_s(a, n)| = 2\sqrt{\frac{1}{a}} \left| \frac{\sin(\omega_c a/4) \sin(\omega_c a/4 + \alpha/2)}{\sin(\omega_c/2)} \right|, n = iT \quad (0-6)$$

Where $\alpha = \phi_{i+1} - \phi_i$ is the phase jump of adjacent code cells and $\tilde{s} = s/|s|$.

According to the formula of the HWT, the frequency of digital modulation signal is reflected by the steady-state value in the same element cycle, and the phase jump between adjacent element is reflected by the transient value. It can be deduced that the Haar

Wavelet Transform have good transient detection capability. So the result of HWT and codes of signals are shown in a same periodic property. The method uses wavelet detection ability of transient to detect the switching point of the adjacent symbols, then estimate the symbol rate through Fourier transform from the pulse sequence which represents the mutations. The method by detecting the presence of symbol rate to distinguish between analog modulation signals and digital modulation signal has been widely used at present.

However, the steady-state value and the transient value of HWT are both close to zero value when $\omega_c a \approx 4n\pi, n=1,2,\dots$, the peak sequence caused by phase jump is not obvious, the code period cannot be gotten, this kind of situation is called the Carrier Frequency Blind Spots^[9]. And there are difficulties in the setting of wavelet scales. Y.T.Chan proposed an improved method to solve the problems of blind spots and wavelet scales difficulties by superposing the results of multi-scale wavelet transform^[2], but it did not resolve the problem essentially, the amount of calculation was greatly increased, the anti-noise ability of the method is poor and the improvement of effect is limited.

In this paper, the frequency of the signal is firstly shifted to the baseband, when $\omega_c \approx 0$, the steady-state value and the transient value of HWT can be expressed as follows:

$$|WT_s(a, n)| \approx \sqrt{a} |\sin(\omega_c a / 4)| \approx 0, \quad (i-1)T + \frac{a}{2} \leq n \leq iT - \frac{a}{2} \quad (0-7)$$

$$|WT_s(a, n)| \approx \frac{2|\sin(\alpha / 2)|}{\sqrt{a}} \left(\frac{a}{2} - |n - iT| \right), \quad iT - \frac{a}{2} \leq n \leq iT + \frac{a}{2} \quad (0-8)$$

As we can see from formula (2-7) and (2-8), the results have nothing to do with carrier frequency ω_c , so there is no invalid wavelet scales problem, the carrier frequency blind spots problem can be solved, then scale 16, the most effective scale of wavelet transform supported in literature^[9], is chosen.

Figure 1(a). Result of AM before and after DDC

Figure 1(b). Result of FM before and after DDC

Figure 2(a). Result of BPSK before and after DDC

Figure 2(b). Result of 16QAM before and after DDC

As the examples shown in Fig.1 and Fig.2, when SNR equal to 1dB, there is no obviously spectral line found in the spectrum of the AM and FM signals' HWT results before and after DDC, in other words, there is no information of symbol rate can be found from analog modulation signals. However, the result of HWT of the BPSK and 16QAM signals are just the opposite. And from the figures of digital modulation signals, the spectral lines in the HWT results after DDC are more obvious and more well-ordered, so the detection of spectral lines will be easier in low signal-to-noise ratio.

It has been confirmed that the improved method gets higher stability and achieves a better effect. Through measuring the interval between the peaks several times and getting the variance of the intervals, the signal can be estimated to be a analog modulation signal or a digital modulation signal.

2.3. Recognition of Analog Modulation Signals

The common analog modulation signals in practical communication systems are AM, FM, LSB, USB, DSB signals. A.K.Nandi proposed a method using the characteristic parameter $\gamma_{\max}$, σ_{ap} , σ_{dp} , P to classify signals AM, DSB, LSB, USB, FM, VSB, AM-FM. It is a common method widely used to classify the analog modulation signals, but the unwrapped phase information which is sensitive to the noise needs to be extracted to calculate parameter σ_{ap} and σ_{dp} , this paper points out that when the signal-to-noise ratio is lower than 10 db, the recognition accuracy rate is very low. And the method can be functional only when some advanced information of the received signal has been known. In this paper, a effective method using the higher order moment of envelope J and the spectrum symmetry P is proposed to classify signals AM, FM, LSB, USB, DSB in the condition of low signal-to-noise ratio.

The received signal $r(t)$ is defined by

$$r(t) = s(t) + n(t) = m(t) \cos[\phi(t)] + n(t) \quad (0-9)$$

where $s(t)$ is the modulated signal, $n(t)$ is a Gaussian white noise variance to σ_n^2 . $s(t)$ and $n(t)$ are independent of each other. $A(t)$ and $\phi(t)$ are respectively the information of amplitude and phase of the modulated signal.

The square of the amplitude envelope $\zeta(t)$ of the received signal $r(t)$ can be defined by

$$\zeta^2(t) = r^2(t) + \hat{r}^2(t) = m^2(t) + 2m(t)a(t) + c^2(t) \quad (0-10)$$

where

$$a(t) = n(t) \cos[\phi(t)] + \hat{n}(t) \sin[\phi(t)] \quad (0-11)$$

$$c^2(t) = n^2(t) + \hat{n}^2(t) \quad (0-12)$$

where $\hat{r}(t)$ is the result of the Hilbert transform of $r(t)$ and $\hat{n}(t)$ is the result of the Hilbert transform of $n(t)$. Because of the independence between $s(t)$ and $n(t)$, second order moments m_2 and fourth-order moments m_4 can be written as follows:

$$m_2 = E[\zeta^2(t)] = E[A^2(t) + 2A(t)a(t) + c^2(t)] = E[A^2(t)] + 2\sigma_n^2 \quad (0-13)$$

$$m_4 = E[\zeta^4(t)] = E\{[A^2(t) + 2A(t)a(t) + c^2(t)]^2\} = E[A^4(t)] + 8\sigma_n^2 E[A^2(t)] + 8\sigma_n^4 \quad (0-14)$$

According to the formula above, it can be deduced that

$$m_4 - 2(m_2)^2 = E[\zeta^4(t)] - 2E^2[\zeta^2(t)] = E[A^4(t)] - 2E^2[A^2(t)] \quad (0-15)$$

It is easily known that the the influence of the noise is eliminated, the normalization is processed to the formula(2-15) by four times the square of the power of $s(t)$, and then define the parameter J as follow

$$J = \frac{m_4 - 2(m_2)^2}{4S^2} = \frac{E[A^4(t)] - 2E^2[A^2(t)]}{4S^2} \quad (0-16)$$

The value of characteristic parameter J for signals AM, DSB, SSB, FM are obviously different, therefore J can be used in classify those signals. The theoretical J value of reference signals are shown in the table I below.

Table 1. Parameters J of Analog Modulation Signals

	theoretical formula	$E[A^4(t)]$	$E[A^2(t)]$	J
AM	$s(t) = [K + m(t)]A \cos(2\pi f_c t + \theta)$	$A^4(K^4 + 3\sigma_m^4 + 6K^2\sigma_m^2)$	$A^2(K^2 + \sigma_m^2)$	$1 - 2K^4 / (K^2 + \sigma_m^2)^2$
FM	$s(t) = A \cos[\phi(t)]$	A^4	A^2	1
DSB	$s(t) = Am(t) \cos(2\pi f_c t + \theta)$	$3A^4\sigma_m^4$	$A^2\sigma_m^2$	0
SSB	$s(t) = A[m(t) + \hat{m}(t)] \cos(2\pi f_c t + \theta)$	$8A^4\sigma_m^4$	$2A^2\sigma_m^2$	-1

And the simulation results as we can see in figure 3 based on MATLAB show that the parameter is effective to classify the reference signals, where the baseband signal $m(t)$ is a zero mean Gaussian white noise after the low pass filter and $n(t)$ is another independent zero-mean Gaussian white noise. Among them, $\sigma_m^2 = 0.5$, $A = 1$, $K = 2$, $f_c = 10\text{KHz}$, $f_s = 8 \times f_c$, the length of the signal data $N_s = 2048$.

Figure 3. Parameter J of Analog Modulation Signals

The results of simulation which evaluates the parameter J of analog modulation signals under different signal-to-noise ratios are summarised in Figure 3, it is clear that the J values of the reference analog modulation signals are different, so the threshold value can be configured as Table 2 below.

Table 2. The Threshold Value of Parameter J

signal	J
AM	$-0.4 < J < -0.1$
FM	$-1 < J < -0.4$
DSB	$J > 0.2$
SSB	$-0.1 < J < 0.2$

Due to the asymmetry of the signal spectrum of SSB signals, the spectrum symmetry P can be used to classify LSB and USB signals, P is defined as

$$P = \frac{P_L - P_U}{P_L + P_U} \quad (0-17)$$

$$P_L = \sum_{i=1}^{f_{cn}} |F_r(i)|^2 \quad (0-18)$$

$$P_U = \sum_{i=1}^{f_{cn}} |F_r(i + f_{cn} + 1)|^2 \quad (0-19)$$

where $F_r(i) = FFT[r(n)]$ is the Fourier transform of the received signal, and $f_{cn} = \frac{f_c \times N_s}{f_s} - 1$. In ideal condition without noises, the spectrum of LSB signal only have the lower sideband ($P_U = 0, P = 1$) and the spectrum of USB signal only have the upper sideband ($P_L = 0, P = -1$).

Figure 4. Parameter P of LSB and USB Signals

From Figure 4, it is clear that LSB and USB signals can be easily classified by parameter P , and the threshold value can be set to 0.

2.4. Recognition of Digital Modulation Signals

Due to the half invariance of cumulants, there is

$$Cum[r(t)] = Cum[s(t)] + Cum[n(t)] \quad (0-20)$$

where $r(t) = s(t) + n(t)$, and $n(t)$ is a Gaussian noise.

Because the result of the cumulants of the Gaussian noise is constantly zero when the cumulants order is in excess of second-order, The cumulants of received signal can be written as

$$Cum[r(t)] = Cum[s(t)] \quad (0-21)$$

So the influence of Gaussian noise can be eliminated when the non-Gaussian signals containing Gaussian noise are transformed to the cumulants domain. High-order cumulants of signals has very good noise resistance performance, so communication signals modulation recognition algorithm based on high-order cumulants has received the widespread attention.

Yu Han uses fourth-order and sixth-order cumulants to classify signals BPSK, QPSK, OQPSK, $\pi/4$ DQPSK, 8PSK, 16QAM, 16APK, 64QAM. Huang Y and Lei J make use of extracting features of higher order cumulants to recognize BPSK, QPSK, 8PSK, 16QAM, 64QAM, 4ASK, 2FSK, 4FSK signals. LV Xin-zheng utilizes second-order, fourth-order, sixth-order cumulants to reach the signals classification of 2ASK, 4ASK, 4PSK, 2FSK, 4FSK. In this paper, the recognition of digital modulation signals including 2ASK, 4ASK, BPSK, QPSK, 8PSK, 16QAM signals using high-order cumulants has been researched.

For a stationary complex random process $X(k)$ with zero-mean, the high-order cumulants can be defined as the follows:

$$C_{20} = Cum[X(k)X(k+l_1)] \quad (0-22)$$

$$C_{21} = Cum[X(k)X^*(k+l_1)] \quad (0-23)$$

$$C_{40} = Cum[X(k)X(k+l_1)X(k+l_2)X(k+l_3)] \quad (0-24)$$

$$C_{41} = Cum[X(k)X(k+l_1)X(k+l_2)X^*(k+l_3)] \quad (0-25)$$

$$C_{42} = Cum[X(k)X(k+l_1)X^*(k+l_2)X^*(k+l_3)] \quad (0-26)$$

$$C_{60} = \text{Cum}[X(k)X(k+l_1)X(k+l_2)X(k+l_3)X(k+l_4)X(k+l_5)] \quad (0-27)$$

$$C_{63} = \text{Cum}[X(k)X(k+l_1)X(k+l_2)X^*(k+l_3)X^*(k+l_4)X^*(k+l_5)] \quad (0-28)$$

when $l_1 = l_2 = l_3 = \dots = 0$, the high-order cumulants can be simplified as follows:

$$C_{40} = M_{40} - 3M_{20}^2 \quad (0-29)$$

$$C_{41} = M_{41} - 3M_{21}M_{20} \quad (0-30)$$

$$C_{42} = M_{42} - |M_{20}|^2 - 2M_{21}^2 \quad (0-31)$$

$$C_{60} = M_{60} - 15M_{20}M_{40} + 30M_{20}^3 \quad (0-32)$$

$$C_{63} = M_{63} - 6M_{20}M_{41} - 9M_{42}M_{21} + 18M_{20}^2M_{21} + 12M_{21}^3 \quad (0-33)$$

where $M_{pq} = E\{X(k)^{p-q}[X^*(k)]^q\}$. The results of high-order cumulants of digital modulation signals are shown in the table as follow

Table 3. High-Order Cumulants of Digital Signals

	C_{20}	C_{21}	C_{40}	C_{41}	C_{42}	C_{60}	C_{63}
2ASK	E	E	$-2E^2$	$-2E^2$	$-2E^2$	$16E^3$	$16E^3$
4ASK	E	E	$-1.36E^2$	$-1.36E^2$	$-1.36E^2$	$8.32E^3$	$8.32E^3$
2PSK	E	E	$2E^2$	$2E^2$	$2E^2$	$16E^3$	$16E^3$
4PSK	0	E	E^2	0	E^2	0	$4E^3$
8PSK	0	E	0	0	E^2	0	$4E^3$
16QAM	0	E	$0.68E^2$	0	$0.68E^2$	0	$2.08E^3$

From Table 3, it can be seen that 2ASK and 2PSK signals' cumulants of each order are the same, so it could not be used to distinguish 2ASK and 2PSK signals by establishing the parameters of its higher order cumulants. Known from the reference^[10], envelope characteristic of signals can be used to make the distinctions between 2ASK and 2PSK signals, two signals are classified as the same class in the following analysis of recognition.

So the classification feature vector is defined by $f_r = [f_1, f_2, f_3]$ to identify those signals.

Where $f_1 = C_{40} / C_{42}$, $f_2 = C_{41} / C_{42}$, $f_3 = C_{63}^2 / C_{42}^3$. As shown in the table I, for signals of different modulation types, the values of the classification feature vector f_r are different as follows

$$f_r = [f_1, f_2, f_3] = \begin{cases} [1, 1, 32] & 2ASK / 2PSK \\ [1, 0, 16] & 4PSK \\ [1, 1, 27.52] & 4ASK \\ [0, 0, 16] & 8PSK \\ [1, 0, 13.76] & 16QAM \end{cases} \quad (0-34)$$

Figure 5. Parameter f_1 of the Reference Digital Modulation Signals

Figure 6. Parameter f_2 of the Reference Digital Modulation Signals

Figure 7. Parameter f_3 of the Reference Digital Modulation Signals

3. Results of Computer Simulations

In this thesis, in order to prove the effectiveness and accuracy of the method mentioned in the paper, supposed the baseband signals of digital modulation signals are random codes and baseband signals of analog modulation signals are Gaussian white noise through a low-pass filter, supposed $f_b = 2\text{KHz}$, $f_c = 16 \times f_b$, $f_s = 8 \times f_c$, $A = 1$, $N = 2048$. the results of computer simulations are shown below:

Figure 8. Accuracy Rate of Recognition between Analog and Digital Modulation Signals before DDC

Figure 9. Accuracy Rate of Recognition between Analog and Digital Modulation Signals after DDC

As shown in Figure 8 and Figure 9, almost all common types of communication signals are researched to compare the performance of new method and traditional method. The method by detecting the presence of symbol rate to distinguish between analog modulation signals and digital modulation signal is effective, and the result of signals after DDC has much better performance than the result before DDC. It can be easily

found that the averaged recognition rate of the improved method is as high as 90% when $SNR \geq 6dB$, there is about 10dB improvement compared to the traditional method.

Figure 10. Accuracy Rate of Analog Modulation Signals Recognition

Figure 11. Accuracy Rate of Digital Modulation Signals Recognition

As shown in Figure 10 and Figure 11, the parameter J and high-order cumulants have a very good performance in noise resistance ability. The Recognition rate remains as high as 90% above with the change of SNR.

Figure 12. Accuracy Rate of all Reference Signals Recognition

It is clear that the recognition algorithm has a good recognition accuracy performance of greater than 90% when $SNR \geq 6dB$. The performance of the algorithm in this paper is much better than others and meanwhile the computational complexity is not high which can satisfy the real-time requirements.

Here is the recognition rate of the reference signals when SNR equals to 10dB in Table 4 below.

Table 4. Recognition Rate of Reference Signals

	AM	FM	DSB	LSB	USB	2ASK/BPSK	4ASK	QPSK	8PSK	16QAM
AM	0.9200	0.0200	0	0	0	0.0600	0	0	0	0
FM	0.0050	0.9950	0	0	0	0	0	0	0	0
DSB	0	0	1	0	0	0	0	0	0	0
LSB	0	0	0	0.9450	0.0550	0	0	0	0	0
USB	0	0	0	0.0150	0.9850	0	0	0	0	0
2ASK/BPSK	0	0	0.0300	0	0	0.9280	0.0420	0	0	0
4ASK	0.0700	0	0	0	0	0.0200	0.9100	0	0	0
QPSK	0	0	0	0	0	0	0	0.9930	0.0070	0
8PSK	0	0	0	0	0	0	0	0	1	0
16QAM	0	0	0	0	0	0.0100	0.0010	0.0520	0.0180	0.9190

4. Conclusion

Communication signal's recognition is an important problem for the electronic countermeasure procedure. In this paper, the method how to classify communication signals including AM, FM, DSB, LSB, USB, 2ASK/BPSK, 4ASK, QPSK, 8PSK, 16QAM is provided. Aiming at the problem of low recognition rate of recognition between analog modulation and digital modulation signals in low SNR, a improved

method is given, which solves the carrier blind point problem and scale selection difficulty problem by down converting the signals to baseband. For the recognition approaches of analog and digital modulation signal, the excellent noise-resistance parameters J and high-order cumulants are introduced. The final result shows that the method has a better recognition result and has a well prospect in communication signal's recognition.

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