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RESEARCH ARTICLE

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Fast identification of digital amplitude modulation level at low signal-to-noise ratio

Abstract In order to rapidly and automatically identify the modulation level of digital amplitude modulated signals at low signal-to-noise ratio (SNR), a method of identifying the modulation levels of *M*-ary quadrature amplitude modulation (*M*-QAM) and *M*-ary amplitude shift keying (*M*-ASK) is proposed. In this method, wavelet transform with the optimal scale is used to identify the modulation levels of *M*-QAM and *M*-ASK signals. The performance of this method was investigated through simulations. Simulation results show that when the SNR is not lower than – 4 dB, the percentage of correct identification of *M*-QAM is higher than 93 %, and when the SNR is not lower than –10 dB, the percentage of correct identification of *M*-ASK is higher than 90 %, using only 100 observed symbols. It shows that this method can rapidly acquire good performance at a low SNR.

Keywords signal processing, modulation identification, wavelet transform

1 Introduction

Modulation identification of communication signals is a technique for identifying the modulation type of a received signal, which has broad prospects in both military and civilian purposes.

Digital amplitude modulation is a frequently used modulation scheme, which for example includes *M*-QAM and *M*-ASK. High-level amplitude modulated signals have an excessive number of symbol status and therefore incline to be disturbed by noise. So it is difficult to identify the high-level amplitude modulated signals at low SNR. A problem arising in the existing methods is that, using the constellation of signals of high level modulation (such as 128-QAM) directly at low SNR cannot acquire a satisfactory performance. Furthermore, too many symbols are needed in those methods to acquire a good performance.

This paper presents a new method of fast identification of *M*-QAM and *M*-ASK signals at low SNR by using wavelet transform (WT) with the optimal scale. The instantaneous amplitude of the signal is abstracted by the optimal-scaled WT, such that the SNR after WT is optimized. Peak detection techniques are also incorporated to identify *M*-QAM and *M*-ASK modulations. Compared with other methods, our method will achieve a much higher correct identification at very low SNR with only a very few number of observed symbols used.

2 Haar wavelet transform of modulated signals

The received waveform $r(t)$ of a communication signal can be expressed by:

$$r(t) = s(t) + n(t) = \tilde{s}(t)\mathrm{e}^{\mathrm{j}(\omega_c t+\theta_c)} + n(t)\,,\quad 0 \leqslant t \leqslant T \tag{1}$$

where $s(t)$ is the modulated complex signal, $n(t)$ is the complex addictive white Gaussion noise (AWGN), $\tilde{s}(t)$ is the envelope, ω_c is the carrier frequency, and θ_c is the carrier phase. For *M*-QAM ($M = K^2$) signal,

$$\begin{gathered}\tilde{s}_{\mathrm{QAM}}(t) = \sum_{i=1}^{N}(A_i + \mathrm{j}B_i)u_T(t - iT),\\ A_i, B_i \in \{2k-1-K, k = 1, 2, \cdots, K\}\end{gathered} \tag{2}$$

For *M*-ASK signal,

$$\tilde{s}_{\mathrm{ASK}}(t) = \sum_{i=1}^{N} A_i u_T(t-iT)\,,\quad A_i \in \{A_1, A_2, \cdots, A_M\} \tag{3}$$

where N is the number of the observed symbols, T is the symbol duration, and $u_T(t)$ is the standard unit pulse with duration T.

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The continuous WT of $s(t)$ is defined as Ref. [1]:

$$W_{\mathrm{s}}(a,\tau)=\int s(t)\Psi_{\mathrm{a}}^{*}(t)\mathrm{d}t=\frac{1}{\sqrt{a}}\int s(t)\Psi^{*}(\frac{t-\tau}{a})\,\mathrm{d}t \tag{4}$$

where a is the scale, τ is the time translation, and the superscript $*$ denotes complex conjugate. $\Psi(t)$ is the mother wavelet, and the baby wavelet $\Psi_{\mathrm{a}}(t)$ is the time scaling and translation of the mother wavelet.

We choose Haar wavelet as the mother wavelet for its simple form, and the Haar wavelet can be expressed as:

$$\Psi(t)=\begin{cases}1, & 0\leqslant t<\dfrac{1}{2}\\ -1, & \dfrac{1}{2}\leqslant t<1\\ 0, & \text{otherwise}\end{cases} \tag{5}$$

When the Haar wavelet is within a symbol period, the WT of an M-QAM signal is given as Ref. [2]:

$$W_{\mathrm{QAM}}(a,\tau)=\frac{4\sqrt{S_i}}{\mathrm{j}\sqrt{a}\omega_{\mathrm{c}}}\sin^2(\omega_{\mathrm{c}}\frac{a}{4})\mathrm{e}^{\mathrm{j}(\omega_{\mathrm{c}}\tau+\theta_{\mathrm{c}}+\phi_i+\frac{\omega_{\mathrm{c}}a}{2})} \tag{6}$$

where $S_i=A_i^2+B_i^2$, and $\phi_i=\tan^{-1}(B_i/A_i)$. Taking the magnitude of Eq. (6) to eliminate the effect of carrier phase, we obtain that

$$\left|W_{\mathrm{QAM}}(a,\tau)\right|=\frac{4\sqrt{S_i}}{\sqrt{a}\omega_{\mathrm{c}}}\sin^2(\omega_{\mathrm{c}}\frac{a}{4}) \tag{7}$$

Similarly, when the Haar wavelet is within a symbol period, the Haar WT of an M-ASK signal is

$$\left|W_{\mathrm{ASK}}(a,\tau)\right|=\frac{4\mathrm{A}_i}{\sqrt{a}\omega_{\mathrm{c}}}\sin^2(\omega_{\mathrm{c}}\frac{a}{4}) \tag{8}$$

3 Modulation identification using WT

Figure 1 shows the magnitudes of M-QAM signals after WT. We can see from the figure that the WTs of M-QAM signals reflect the instantaneous amplitudes of the signals. The WTs of 16-QAM, 64-QAM and 128-QAM signals have 3, 9, and 16 DC levels, respectively. Peaks occur at the symbol transitions. After the WT magnitude of the signal is obtained, we filter it with a median filter and an average filter in succession to eliminate the peaks and reduce noise.

Then we compute the histogram of the magnitude sequence to implement the identification. Since the histograms of the WTs of various QAM signals have various numbers of peaks, the value M can be determined using the histogram of the WT of the signal.

Similarly, the WT of M-ASK is a multi-step function with M different levels. The approach of identifying M-ASK is also analogous to that of M-QAM.

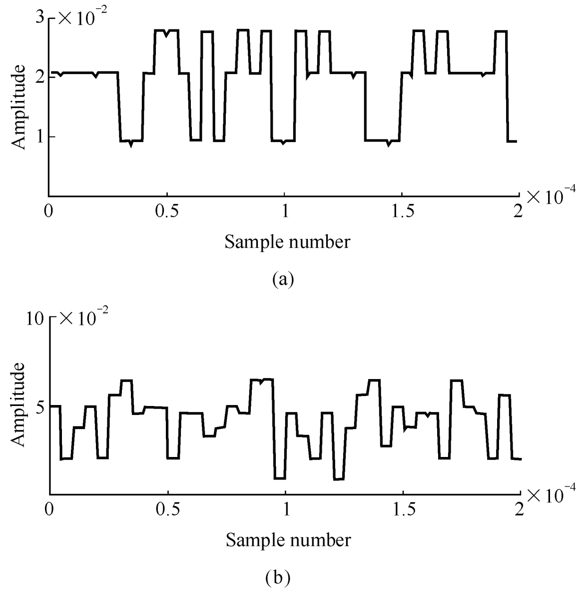

Fig. 1 The WT magnitudes of M-QAM signals. (a) 16-QAM; (b) 64-QAM

4 Optimization of the WT scale

The existing literatures of modulation identification using WT have not investigated the influence of the WT scale. However, for the amplitude modulated signals, the SNR gain after WT strongly depends on the WT scale. The identification of signals with high SNR is easier, since they have larger amplitude variance and the peaks of the histogram of their |WT| are more distinct. In this paper, we optimize the SNR gain after WT by selecting an optimal WT scale, whereby we acquire a preferred performance.

Here we will analyze the SNR gain of the M-QAM signal after WT, and the M-ASK case is similar.

In Eq. (4), let $t=kT_{\mathrm{s}}$, $\tau=nT_{\mathrm{s}}$, $a=\hat{a}T_{\mathrm{s}}$, we can obtain that

$$W(a,\tau)=\frac{1}{\sqrt{\hat{a}f_{\mathrm{s}}}}\sum_k s(k)\Psi^{*}(\frac{k-n}{\hat{a}}) \tag{9}$$

wherein

$$\frac{1}{\sqrt{\hat{a}f_{\mathrm{s}}}}\Psi(\frac{k-n}{\hat{a}})=\begin{cases}\dfrac{1}{\sqrt{\hat{a}f_{\mathrm{s}}}}, & k=n,n+1,\cdots,n+\dfrac{\hat{a}}{2}-1\\ -\dfrac{1}{\sqrt{\hat{a}f_s}}, & k=n+\dfrac{\hat{a}}{2},\cdots,n+\hat{a}-1\\ 0, & \text{else}\end{cases} \tag{10}$$

then

$$\left|W_{\mathrm{QAM}}(\hat{a},n)\right|=\frac{4\sqrt{S_i}}{\sqrt{\dfrac{\hat{a}}{f_{\mathrm{s}}}}2\pi f_{\mathrm{c}}}\sin^2(\frac{2\pi f_{\mathrm{c}}\dfrac{\hat{a}}{f_{\mathrm{s}}}}{4}) \tag{11}$$

wherein $f_c = \omega_c / 2\pi$. Because the noise is AWGN, and the WT energy in Eq. (10) is $1/f$, the noise power after Haar WT is $1/f_s$ of the power before WT [3], namely:

$$P_{n\mathrm{WT}} = \frac{P_n}{f_s} \tag{12}$$

wherein P_n is the noise power before WT, and $P_{n\mathrm{WT}}$ is the noise power after WT.

From Eq. (11), we can obtain that

$$P_{s\mathrm{WT}}(\hat{a}, n) = \left(\frac{4}{\sqrt{\frac{\hat{a}}{f_s} 2\pi f_c}} \sin^2 \left(\frac{2\pi f_c \frac{\hat{a}}{f_s}}{4} \right) \right)^2 P_s \tag{13}$$

From Eqs. (12) and (13) we can derive that

$$R_{\mathrm{WT}} = \frac{P_{s\mathrm{WT}}}{P_{n\mathrm{WT}}} = \frac{4 f_s^2}{\hat{a}\pi^2 f_c^2} \sin^4 \left(\frac{\pi \hat{a} f_c}{2 f_s} \right) R \tag{14}$$

wherein $R = P_s / P_n$ is the SNR before WT. So the SNR gain after WT is

$$G_{\mathrm{SNR}} = \frac{R_{\mathrm{WT}}}{R} = \frac{4}{\hat{a}\pi^2} \frac{f_s^2}{f_c^2} \sin^4 \left(\frac{\pi \hat{a}}{2} \frac{f_c}{f_s} \right) \tag{15}$$

The SNR of the signal after WT will be increased only when $G_{\mathrm{SNR}} > 1$, so that the correct identification will be higher than that using the signal itself. From Eq. (15) we know that the scale $\hat{a}$ has great effect on the SNR gain. After the approximate ratio of carrier frequency f_c and the sampling frequency f_s is calculated, we can obtain the relationship between the SNR gain G_{SNR} and the scale $\hat{a}$. Take $f_c / f_s = 1/50$ as an example, the relationship between the SNR gain G_{SNR} and the scale $\hat{a}$ is shown in Fig. 2.

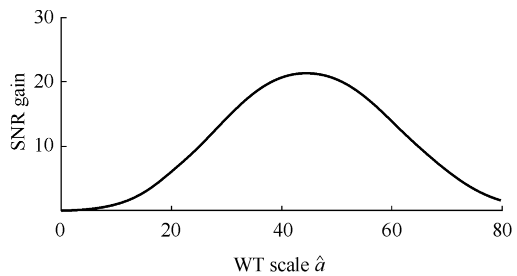

Fig. 2 Relationship between SNR gain and WT scale

We can see from Fig. 2 that there exists an optimal scale, that is, when $\hat{a} = 44$ the SNR gain is optimized to a maximum value of 21.4. So $\hat{a} = 44$ is the optimal WT scale.

Figure 3 shows the waveforms of 2-ASK signals before and after optimal-scaled WT, at the SNR of –8 dB. These two sequences are both processed with an average filter. As shown in Fig. 3(a), when the SNR is –8 dB, the 2-ASK signal without WT is totally deteriorated by the noise, and the two amplitude levels can hardly be identified. While in Fig. 3(b) after WT, the two different amplitudes of the signal can still be distinguished, and each symbol can be

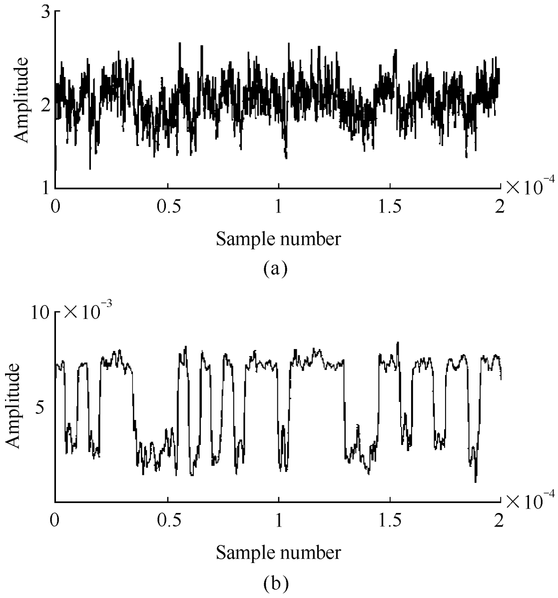

Fig. 3 Waveforms of 2-ASK signals before and after WT. (a) Before WT; (b) After WT

differentiated easily.

In order to further explain how much the scale can influence the identification, Fig. 4 compares the performance of the *M*-QAM identification method using the optimal scale with those using other scales. In Fig. 4, the *x*-axis is for the SNR, and the *y*-axis for the average correct identification of 64-QAM and 128-QAM in the case of $f_c / f_s = 1/50$. Figure 4 compares the performances of using $a = 44T_s$ (the optimal scale), $24T_s$, and $64T_s$. It can be seen that the WT scale significantly affects the identification performance.

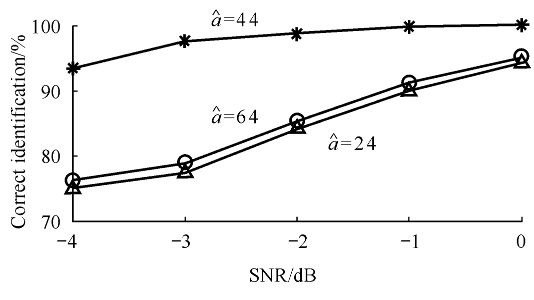

Fig. 4 The influence of WT scale on the performance of identifying *M*-QAM

5 Simulation results

Simulations were carried out for *M*-QAM (*M*=16, 64, 128) and *M*-ASK (*M*=2, 4, 8) signals corrupted by the complex AWGN to investigate the performance of our method. The relationship between the symbol rate, the carrier frequency, and the sampling frequency was $f_d / f_s = 1/500$ and $f_c / f_s = 1/50$. The optimal WT scale according to our method was $a = 44T_s$. The length of the median filter and the average filter were 95 and 50, respectively. Only 100 symbols were used for each simulation, and the results were based on the average of 1 000 simulations. Table 1 and Table 2 show the percentage of correct identification for *M*-QAM and for *M*-ASK signals, respectively. It can be seen, when the SNR is not lower than –4 dB, the percentage of correct identification for *M*-QAM is higher than 93 %; when the SNR is not lower than –10 dB, the percentage of correct identification for *M*-ASK is higher than 90 %.

Table 1 Percentage of correct identification for *M*-QAM signals

SNR/dB	16-QAM	64-QAM	128-QAM
–4	1.000	0.935	0.931
–3	1.000	0.955	0.971
–2	1.000	0.980	0.973
–1	1.000	1.000	0.993
0	1.000	1.000	1.000

Table 2 Percentage of correct identification for *M*-ASK signals

SNR/dB	2-ASK	4-ASK	8-ASK
–10	0.921	0.915	1.000
–8	0.976	0.977	1.000
–6	1.000	1.000	0.992
–4	1.000	1.000	0.998
–2	1.000	1.000	1.000

Figure 5 shows the comparison between our method and the other methods for QAM identifications [4–6]. Label 1 is the average identification for 16-QAM and 32-QAM in Ref. [4] using 1 024 symbols. Label 2 is the identification for 16-QAM in Ref. [5] using 1 000 symbols. Label 3 is the average identification for 4-QAM, 16-QAM, 32-QAM and 64-QAM in Ref. [6] using 512 symbols. Label 4 is the average identification for 16-QAM, 64-QAM and 128-QAM in our method using only 100 symbols.

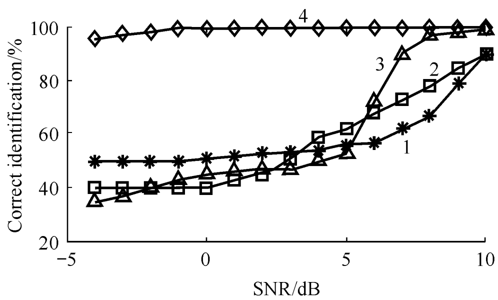

Fig. 5 Comparison performances of QAM identifications using different methods

It can be seen from Fig. 5 that the correct identification at low SNR was significantly increased using the method proposed in this paper. Furthermore, the number of the observed symbols used is only $1/5 - 1/10$ of that in other methods, which is conducive for acquiring the identification results in real time.

In order to further illuminate how much the observed symbol number can affect the identification performance, Fig. 6 shows the average identification of *M*-QAM (*M*=16, 64, 128) with various numbers of observed symbols using our method with the SNR of –4 dB. From Fig. 6 we know that when the observed symbol number increases, the performance of our method will be further improved.

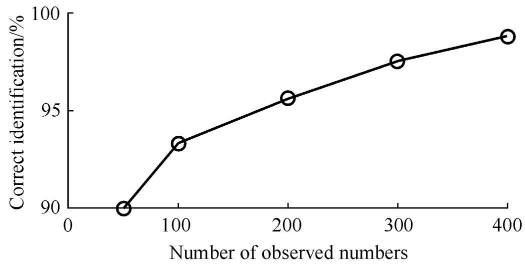

Fig. 6 Performance vs. number of observed symbols

6 Conclusions

We have proposed a fast modulation identification method for *M*-QAM and *M*-ASK signals using optimal-scaled wavelet transform. First we compute the wavelet transform of the signal with the optimal scale. Then we take the histogram of the magnitude of the resultant WT sequence. Finally, peak detection techniques are used to identify the modulation scheme used. Simulation results show that when the SNR is not lower than –4 dB, the correct identification for *M*-QAM is higher than 93 %, and when the SNR is not lower than –10 dB, the correct identification for *M*-ASK is higher than 90 %. The method proposed in this paper acquired very good performance with only 100 symbols used. When the number of the observed symbols is increased, the performance of this method will be further improved.

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