A Blind Recognition Algorithm for Digital Amplitude Modulated Signals

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Abstract. A blind recognition Algorithm of amplitude modulation-ASK and QAM signals is proposed in this paper. Without requiring any prior information of the accepted signal, this algorithm employs the instantaneous amplitude of the incoming signal to recognize the modulation order, i.e., M, using the clustering centers of the amplitude. It is found that this new algorithm is practical and steady in recognition amplitude modulation signal in the presence of AWGN.

1. Introduction
Automatic modulation recognition is intermediate step between signal detection and demodulation. It is widely used in military and civilian communication. In non-cooperative communication situations, many parameters of the transmitted signal are unknown to the receiver, i.e., the recognition algorithm needs to be Blind Modulation Recognition (BMR). From the theory of BMR being proposed, many researchers have done a lot of work to get good recognition performance in classifying amplitude modulation. Some researchers aimed to identify 2ASK and 4ASK signals [1-2]. For QAM signals, researchers also have done a lot of work [3-5]. In [3], an algorithm based on signal constellation was proposed to identify QAM signals, while this algorithm was a bit complicated to be carried out because it required channel equalization. In [4], the author employed clustering algorithm to classify MQAM signals, however, this method couldn’t identify high-order modulation. [5] modified this algorithm and extended it to high-order QAM signals. Although much work was done, there are still some problems in amplitude modulation signals recognition. On one hand, most researchers take raised cosine filter as the transmitting filter, which is not practical in real communication systems like mobile and satellite communications; on the other hand, few papers refer to ASK recognition and this phenomenon can’t be interpreted for the excuse of the less utilization of ASK signals because in non-cooperative conditions any types of signal are probable to be used [11].

In this paper, a more practical BMR algorithm to classify MASK and MQAM signals is proposed. This algorithm doesn’t require any prior knowledge of signal parameters but estimate carrier frequency, baud rate and timing error. With these estimated parameters, subtractive clustering algorithm is performed to extract clustering centers of the instantaneous amplitude, consequently modulation type is identified from the numbers of cluster centers.

2. Signal model [5]
For amplitude modulation--MASK and MQAM, the baseband complex envelop of the received signal can be expressed as
\[ r(t) = \left( \sum_{k=-\infty}^{\infty} c_k g_{f_t} (t - kT_b - \epsilon(t)T_b) \right) \exp\left[j(2\pi f t + \theta)\right] + n(t) \] (1)

Where \( c_k = a_k + jb_k \) represents the transmitted symbol.

For MASK, \( a_k = md, m = 0,1,\ldots, M - 1, b_k = 0 \),
For MQAM, \( a_k, b_k = (2m - 1 - \sqrt{M})d, m = 1,2,\ldots, \sqrt{M} \).

\( d \) denote the Euclidean distance of adjacent constellation points, which can be set as 1.0 in simulation, because it is not related to the realization of the algorithm, \( g_{f_t} \) the impulse response of root-raised cosine filter, \( T_b \) the symbol period, \( \epsilon(t) \) the normalized timing error, \( \Delta f \) the remaining carrier-frequency deviation, \( \theta \) the initial phase of the carrier, and \( n(t) \) the zero-mean AWGN.

3. Algorithm formulation

The algorithm is shown in figure 1. First, we sample the continuous signal \( r(t) \) and get the discrete-time sequence, which is denoted as \( r(n) \). Then this sequence is used to estimate carrier frequency, baud rate and timing error. Because the shaping filter used by the transmitter is root-raised cosine filter, it is needed to use another root-raised cosine filter to perform matching filtering. Since the match filter is low pass filter, we need to down converter the input signal before matching filter, which means the carrier frequency must be known. So we estimate the carrier frequency of the signal and employ digital down converter (DDC). After DDC and getting baud rate, we adjust the sampling rate to integral multiples of the baud rate, and perform interpolation \[9\] according the timing error and baud rate. In order to overcome the influence of remaining carrier frequency, we utilize the instantaneous amplitude of the signal as the classification feature. With envelope of the signal, the subtractive clustering algorithm is applied to obtain the cluster center, the numbers of which can be used as the classification feature. For a good cluster performance on MASK and MQAM, we first classify them into two categories, one is ASK modulation and the other belongs to QAM modulation. Then, multi-radius clustering algorithms are used in the both two categories respectively.

3.1 Baud rate estimation

In this section, we adopt the algorithm in \[7\] to estimate baud rate. However, the baud rate estimation of MASK signals isn’t referred to in this paper. According to the following research done by other scholars, it can be found that the method utilized in \[7\] can also be employed to estimate the baud rate of MASK signals under the circumstance of root-raised cosine shaping pulse. Here we don’t enumerate the detailed reason, instead, we introduce the core idea of this algorithm only.

The squared envelope signal is calculated as

\[ s_e(t) = \sum_k (a_k^2 + b_k^2) g_{f_t}^2 (t - kT_b) \] (2)
Then, \( s_e(t) \) can be written as

\[
s_e(t) = u(t) + n_e(t)
\]  

(3)

Where \( u(t) \) and \( n_e(t) \) are given as

\[
u(t) = E\{s_e(t)\} = (A + B)\sum_k g_{ts}^2(t - kT_b)
\]  

(4)

\[
n_e(t) = \sum_k \sum_{j\neq k}(a_j a_k + b_j b_k)g_{ts}^2(t - jT_b)g_{ts}^2(t - kT_b) + \sum_k(a_k^2 + b_k^2 - A - B)g_{ts}^2(t - kT_b)
\]  

(5)

The Fourier transform of \( u(t) \) is given by

\[
U(f) = \frac{A+B}{T_b} \sum_l [G(f) * G(f)] \delta(f - \frac{1}{T_b})
\]  

(6)

Where \( G(f) \) represents Fourier transform of \( g_{ts}^2(t) \), * denotes convolution. In eqn.5, for the reason that \( G(f) = 0 \) for \( |f| > \frac{1}{T_b} \), the discrete spectral lines only appear at \( l = 0, \pm 1 \) which correspond to the DC and the baud rate components respectively. From what is talked above, it is obvious that the baud rate of the input signal can be estimated by detecting a single peak frequency component within the pre-assigned frequency range which includes the baud rate. If the input signal bandwidth is \( B_w \), then the frequency range to be observed is given by \( B_w / 2 \sim B_w \) because \( B_w / 2 \leq 1/T_b \leq B_w \).

Even if the Fourier transform can be used to estimate the baud rate, the estimated performance could not be assured only through it, because the frequency resolution is affected by the data length and sampling rate. To obtain high resolution, a big data length is needed, which would cause high calculation burden. So as to solve this problem, we can use chirp Z-transform (CZT) [3]. Compared to FFT, the CZT can achieve better frequency resolution in spectrum for a selected frequency range, but the calculation burden doesn’t increase much. The baud rate estimation algorithm using CZT consists of the following steps:

1) Obtain the squared envelope of input signal \( |r(t)|^2 \);
2) Compute FFT of \( |r(t)|^2 \), which is given by \( R(f) \), to estimate the bandwidth \( B_w \);
3) Use \( R(f) \) to get the rough estimation of baud rate, by searching the single peak of \( R(f) \) in the range of \( B_w / 2 \leq 1/T_b \leq B_w \), the baud rate obtained in this step is represented as \( \hat{r}_b \);
4) Perform CZT to zoom in on a narrow band section \((\hat{r}_b(1-\beta) \sim \hat{r}_b(1+\beta))\) of the frequency spectrum of \( |r(t)|^2 \), where \( \beta \) can be chosen as 0.05;
5) Detect the peak frequency of the CZT, which is the estimation of baud rate.

3.2 Carrier frequency estimation [4]

The spectrum of ASK signals would show an impulse which corresponds to the carrier frequency. The quadruplicated QAM signals would also show an impulse which correspond to four times of carrier frequency. Using this characteristic to get the rough estimation of carrier frequency, and then take the similar steps mentioned in 3.1 to obtain precise estimated value of carrier frequency.
3.3 Timing error estimation

We adopt the squared timing error estimation algorithm in [8] to estimate timing error. The procedure is performed as figure 2.

As is illustrated in figure 2, calculate the square spectrum of the envelope, and extract instantaneous phase to get the estimated timing error. It can be proved that the normalized phase \( \hat{\epsilon} = \frac{1}{2\pi} \arg(X_m) \) is an unbiased estimation for the true timing error \( \epsilon \).

4. Clustering algorithm

Since the presence of AWGN, and the influence of the shaping filter, the instantaneous amplitudes are distributed dispersely. Then the subtractive algorithm [6] is performed to detect the numbers of cluster centers. The density measure of data point \( x_i \) is defined as

\[
D_i = \sum_{j=1}^{N} \exp\left(-\frac{\|x_i - x_j\|^2}{(r_a/2)^2}\right)
\]  

Where \( r_a \) defines a district near \( x_i \), those data points beyond this district has little influence on this density measure.

After getting the density measures of each pointer, the pointer which has the largest density value will be chosen as the first cluster center, which can be marked as \( x_{c1} \), and its density measure is presented by \( D_{c1} \). Then the density measure of each data point is revised as

\[
D_i = D_i - D_{c1} \exp\left(-\frac{\|x_i - x_{c1}\|^2}{(r_b/2)^2}\right)
\]  

\( r_b \) defines a neighborhood that remarkable reductions density measure. Usually, \( r_b \) is larger than \( r_a \) to insure those cluster centers are not too close to each other. The data points near the first cluster center will has significantly reduced density value, which ensures those points are impossible to be selected as the next cluster center. After updating the density function, chose the data point with the largest density measure as the next cluster center. This process is repeated until all the points are within the neighborhood district of the cluster centers.

For MASK and MQAM signals, signals with different modulation orders have different amplitude values. The instantaneous amplitudes of 2ASK, 4ASK, 8ASK, 16ASK, 16QAM, 32QAM, 64QAM signals have 2, 4, 8, 16, 3, 5, 9 possible values respectively. However, to realize the aim of classifying these signals, some problems would occur: 1) from the possible values of these signals, it is easy to find that some signals have very close numbers of amplitude values, which makes it hard to identify those signals effectively; 2) a fixed radius and a fixed threshold are not sufficient to identify all these signals. In consideration of problems mentioned above, we need to classify those signals into two kinds first, and then employ multi-radius method to classify those signals within each kind, which will be interpreted in next section.
5. Recognition procedure
The largest difference between MASK and MQAM signals is that MQAM signals are zero-meaned, while MASK signals are not. We extract this characteristic as the classifying feature. Implement FFT of the received signal, an impulse will appear in the spectrum of MASK signals and this impulse correspond to carrier frequency exactly. After classifying these signals into two kinds, i.e. MQAM and MASK, the algorithms to identify modulation types within each kind can be applied. In the classification of the two kinds of signal, subtractive clustering algorithm will be used respectively. And we select the average value of the amplitudes as the threshold to classify the adjacent two signals. As is mentioned in the former section, we use multi-radius, and multi-threshold method, i.e. for MQAM, cluster radius set is selected as \( \{r_n\} = \{0.225, 0.12, 0.08\} \), and the threshold set is \( \{th_n\} = \{3, 7, 13\} \) and for MASK, cluster center is selected as \( \{r_n\} = \{0.5, 0.26, 0.11, 0.0625\} \), and threshold set is selected as \( \{th_n\} = \{2, 5, 12, 24\} \). Then the classification procedure can be performed as follows (take MQAM signals as an example):

1) Assume the modulation type to be the simplest one (16QAM);
2) Perform clustering algorithm with the largest radius, i.e. 0.225;
3) If the numbers of cluster centers is no more than 3, the hypothesis is true, if not, the hypothesis is false;
4) Substitute radius with the next one;
5) The process is iterated until nth number of centers is no more than nth threshold.

6. Simulation and results
To evaluate the performance of the algorithm proposed, we choose seven types of amplitude modulated signals (2ASK, 4ASK, 8ASK, 16ASK, 16QAM, 32QAM, 64QAM) which are deteriorated by AWGN. The normalized symbol rate is 1.0, and sampling rate and carrier frequency are 16.85 and 0.5 respectively. Transmitting filter is root-raised cosine filter, and the roll-off factors is chosen as 0.35. From [10], we know that the roll-off factor has little influence on the performance on this two kinds of signals, for this reason we choose the roll-off factor of match filter as 0.5. The performance of recognition is shown in figure 3. 500 Monte Carlo trials are carried out for each combination of modulation type, SNR value, and 600 symbols are used for each signal. It can be found in figure 3 that recognition performance improves with an increase in SNR.

![Figure 3. Performance of proposed algorithm](image-url)
7. Conclusions
A practical algorithm for classifying amplitude modulation has been developed to identify MQAM and MASK signals in AWGN channel. The proposed algorithm has achieved reasonably good results in simulation. This algorithm requires no prior knowledge of the signal parameter. In contrast with most other researchers, this algorithm is more practical for the reason of using root-raised cosine shaping filter and expands the recognition range to ASK modulation. This method can be used in practical non-cooperative communication fields.

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