

# Study of Blind Demodulation Algorithm based on Sequential Detection of Unknown Constellation QAM

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## **Abstract**

*In this paper, we propose a novel on-line blind demodulation algorithm for Quadrature Amplitude Modulation (QAM). The proposed approach can demodulate QAM signal without constellation knowledge, and reach the theoretical optimal performance under the constraint of sequential detection. Numerical simulations are provided to validate the analytical results. Results show that when iterations are large enough, the bit error rate (BER) of the proposed approach can be close to the optimal demodulation algorithm.*

**Keywords:** modulation classification, blind demodulation, QAM, detection theory

## **1. Introduction**

In the non-cooperative communication scenario, many modulation parameters, especially modulation modes, are unknown. Furthermore, with the development of software defined radio (SDR), self-adaptive modulation (like COFDM) and heterogeneous communication systems are becoming important directions for the future research [1-3]. All the above-mentioned situation lead to invalidation of classical demodulation approaches. Hence the study of blind (or semi-blind) demodulation is of great practical and theoretical importance.

The general process of existing blind demodulation methods can be classified into two steps, that is parameter estimation and demodulation [4-5]: In those algorithms, essential parameters would be estimated first. Then traditional demodulation algorithms would be used to extract source information. However, it should be pointed out that the above process has two problems: first, the separation of parameter estimation and demodulation usually results in sub-optimal performance; second, the signal used in parameter estimation cannot be demodulated.

For solving these problems, his paper is focused on the contribution to introduce a novel approach which can minimize symbol error probability by using iterative algorithm based on sequential detection without parameter estimation. Also the structure of the receiver will be provided.

The structure of the paper is as follows: the blind demodulation iteration algorithm based on sequential detection will be proposed in Section 2. The analysis of performance with simulation will be made in Section 2. In Section 4, conclusion will be made.

## **2. Algorithm**

The proposed demodulation algorithm is based on sequential detection. That is whenever new symbol enters the receiver, the proposed algorithm can just use current- symbol and the

knowledge obtained from previous symbols to demodulate the current symbol in real-time, which ensures an on-line demodulation structure.

Without loss of generality, some assumptions will be given first:

- (1) The number of received symbols is  $N$ .
- (2) The identifiable modulation mode assemble is  $M = \{M_1, M_2, \dots, M_L\}$ , the number of whose elements is  $\overline{M} = L$ , and its index assemble is  $\underline{L}$ , that is  $\forall l \in \underline{L}, M_l \in M$ .
- (3) The hypothesis test assemble of the  $n$ th symbol arriving at the receiver is  $H_n = \{H_{n,1}, H_{n,2}, \dots, H_{n,W}\}$ , the number of whose elements is  $\overline{H}_n = W$ .
- (4) Assuming the received signal is influenced by additive white Gaussian noise, the single-band power spectrum density is  $N_0$ .
- (5) Perfect synchronization has be done before the algorithm.
- (6) The power of both received signal and noise is already known.
- (7)  $X$  represents all the prior knowledge known by the receiver.

Assuming that the hypothesis for the  $n$ th symbol is  $H_{n,i}$ , then we can get the posterior probability from [3]

$$\begin{aligned} \Pr(H_{n,i} | \overline{r}_n X) &= \sum_{l \in \underline{L}} \Pr(M_l | \overline{r}_n X) \Pr(H_{n,i} | \overline{r}_n M_l X) \\ &= \sum_{l \in \underline{L}} \Pr(M_l | \overline{r}_{n-1} r_n X) \Pr(H_{n,i} | \overline{r}_{n-1} r_n M_l X) \end{aligned} \quad (1)$$

where  $r_n$  is the  $n$ th received data. Using Bayes Theorem, equation (1) can be written as:

$$\begin{aligned} \Pr(H_{n,i} | \overline{r}_n X) &= \frac{\Pr(r_n | H_{n,i} X)}{\Pr(r_n | \overline{r}_{n-1} X)} \\ &\cdot \sum_{l \in \underline{L}} \Pr(M_l | \overline{r}_{n-1} X) \Pr(H_{n,i} | M_l X) \end{aligned} \quad (2)$$

Let

$$MC_{n,l} = \Pr(M_l | \overline{r}_n X) \quad (3)$$

$$LH_{n,i} = \Pr(r_n | H_{n,i} X) \cdot (2\pi\sigma^2)^{-\frac{1}{2}} \quad (4)$$

$$B_{i,l} = \Pr(H_{n,i} | M_l X) \quad (5)$$

where  $\sigma^2 = \frac{N_0}{2}$ . Substitute equation (3)-(5) into equation (2), hence

$$\Pr(H_{n,i} | \overline{r}_n X) = \frac{LH_{n,i}}{(2\pi\sigma^2)^{\frac{1}{2}} \Pr(r_n | \overline{r}_{n-1} X)} \sum_{l \in \underline{L}} MC_{n-1,l} \cdot B_{i,l} \quad (6)$$

Since the impact of white Gaussian noise, then

$$\Pr(r_n | H_{n,i} X) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{|r_n - d_i|^2}{2\sigma^2}\right) \quad (7)$$

Substitute equation (7) into equation (4) and we obtain

$$LH_{n,i} = \exp\left(-\frac{|r_n - d_i|^2}{2\sigma^2}\right) \quad (8)$$

Final detection statistics can be obtained from the simplification:

$$mD(H_{n,i}, r_n) = LH_{n,i} \sum_{l \in \underline{L}} M_{n-1,l} \cdot B_{i,l} \quad (9)$$

As the formulas mentioned above,  $MC_{n,l}$  means the posterior knowledge of the  $l$  th modulation mode calculated by the receiver according to the data received.  $LH_{n,i}$  is the level of confidence under the  $i$  th hypothesis.  $B_{i,l}$  stands for the probability of the appearance of different symbols under different modulation mode, which is independent with received data. Therefore the computation of test statistics is equivalent to calculation of variables above.

Based on the property of  $MC_{n,l}$ , the following expression can be obtained:

$$\begin{aligned} MC_{n,l} &= \Pr(M_l | \overline{r_n} X) \\ &= \Pr(M_l | \overline{r_{n-1}} r_n X) \\ &= \Pr(M_l | \overline{r_{n-1}} X) \frac{\Pr(r_n | M_l X)}{\Pr(r_n | \overline{r_{n-1}} X)} \end{aligned} \quad (10)$$

Since

$$\Pr(r_n | M_l X) = \sum_{i=1}^W \Pr(H_{n,i} | M_l X) \Pr(r_n | H_{n,i} X) \quad (11)$$

$$\begin{aligned} \Pr(r_n | \overline{r_{n-1}} X) &= \sum_{i=1}^W \Pr(r_n | H_{n,i} X) \\ &\cdot \left[ \sum_{l \in \underline{L}} \Pr(M_l | \overline{r_{n-1}} X) \cdot \Pr(H_{n,i} | M_l X) \right] \end{aligned} \quad (12)$$

Substitute equation (4)-(5), (11)-(12) into equation (10), thus the iteration formula of  $MC_{n,l}$  is

$$MC_{n,l} = MC_{n-1,l} \frac{\sum_{i=1}^W LH_{n,i} \cdot B_{i,l}}{\sum_{i=1}^W LH_{n,i} \left[ \sum_{l \in \underline{L}} MC_{n-1,l} \cdot B_{i,l} \right]} \quad (13)$$

Generally, the receiver has no prior knowledge about demodulation mode. So assuming the elements of identifiable modulation mode assemble has equal probability is reasonable, that is

$$MC_{0,l} = \frac{1}{L} \quad \forall l \in \underline{L} \quad (14)$$

Substitute equation (14) into equation (13), as the initial value of iteration,  $MC_{n,l}$  can be achieved.

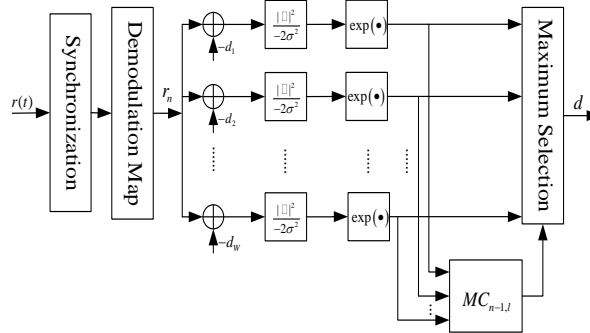
According to the MAP criterion, the output  $d_n$  needs to meet the expression:

$$d_n = \arg \left\{ \max_{H_{n,i}} \left[ mD(H_{n,1}, r_n), \dots, mD(H_{n,W}, r_n) \right] \right\} \quad (15)$$

In conclusion, the algorithm flow is as follows:

(1) Calculate the Euclidean distance between received data  $r_n$  and all the local samples  $d_i, i = 1, 2, \dots, W$ ,  $LH_{n,i}$  can be achieved.

- (2) Compute the test statistics  $mD(H_{n,i}, r_n), i = 1, 2, \dots, W$  by using  $MC_{n-1,l}$  and  $B_{i,l}$ .
- (3) Select the symbol that results in maximum of test statistics.
- (4) Compute  $MC_{n,l}$  using  $r_n, MC_{n-1,l}$  and  $B_{i,l}$  as the assistant information. The receiver block diagram is shown as Figure 1.



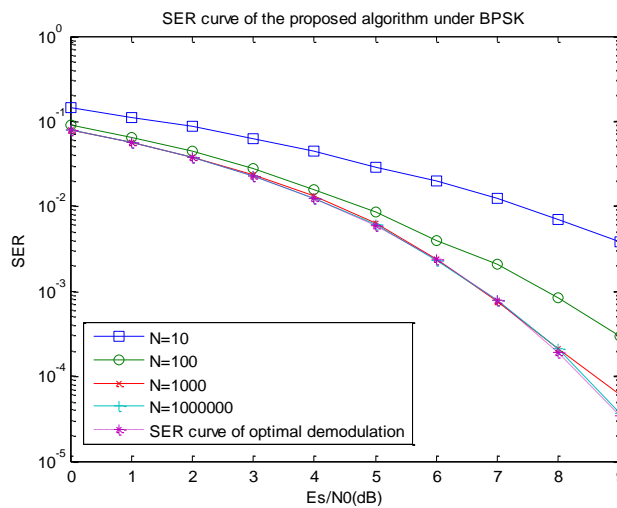
**Figure 1. Framework of blind demodulate receiver**

To reduce the computation complexity of  $MC_{n,l}$ , detail information can be found in the references[6-8].

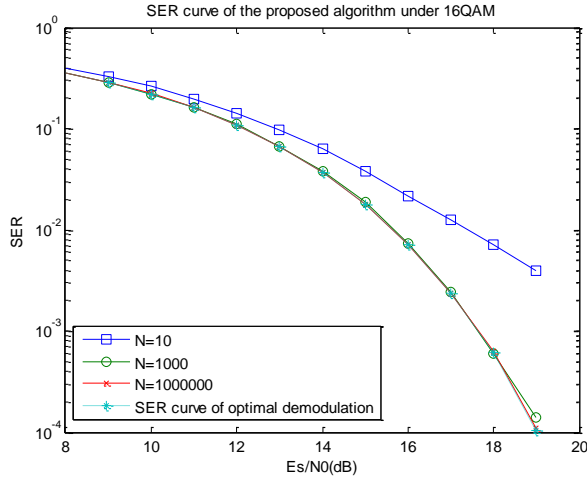
### 3. Simulation and Performance Analysis

Based on the algorithm provided in Section 2, simulation and contrast analysis of algorithm performances have been done by using simulation software MATLAB.

The simulation parameters are as follows: demodulation modes contain  $A = \{BPSK, QPSK, 4ASK, 16QAM\}$  and  $B = \{BPSK, QPSK, 8PSK, 4ASK, 16QAM, 64QAM, 256QAM\}$  respectively [9-10]; carrier frequency  $f_c = 10KHz$ , carrier initial phase  $\theta_c = 0$ , code rate  $R_b = 10B$ , sampling frequency  $f_s = 100KHz$ , modulation mode of transmitter is BPSK which can be seen as the simplest mode of QAM and 16QAM, iteration number  $N$  include 10, 100, 1000, 1000000 respectively. The symbol error rate (SER) can be seen from Figure 2.



**Figure 2. SER curves of the algorithm under BPSK**



**Figure 3. SER curves of the algorithm under 16QAM**

It can be seen from the Figures 2 and 3 that, when the modulation modes is BPSK or 16QAM, the SER of the proposed algorithm is higher than the optimal demodulation method of BPSK or 16QAM with known constellation respectively. While with the growth of iteration number  $N$ , the SER of the proposed one tends to approach the optimum demodulation method. When the iteration is large enough, the performance of the proposed algorithm converge to the optimal demodulation method.

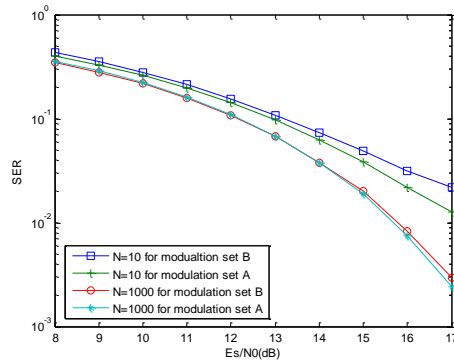
It also can be seen from the Figures 2~3 that, with the increasing of SNR, the number of iteration symbol also increases in order to achieve the same SER level of regular optimal demodulation. It is because that demodulator performance is impacted by the additive white Gaussian noise.

According to (16), given

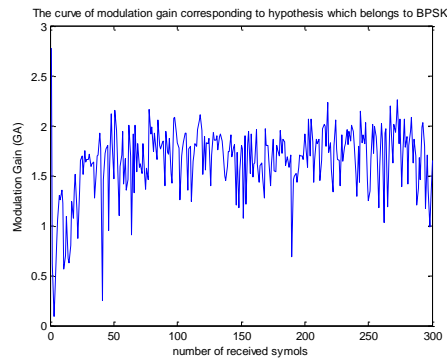
$$Ga_{n,i} = \ln \left( \sum_l M_{n-1,l} \cdot B_{i,l} \right) \quad (16)$$

where  $Ga_{n,i}$  is recognized as a kind of Modulation Gain (MG). This function reflects the volume of constellation knowledge which can be learned from received signals. The curves of normalized MG for different hypothesizes is given in Figure 5~6, where  $E_s / N_0 = -9dB$  and the modulation mode is BPSK.

It can be seen from comparing Figure 5 and Figure 6 that the MG corresponding to hypothesis which belongs to BPSK is fluctuating over a narrow range with the growth of the number of symbols. Inversely, the MG corresponding to hypothesis which doesn't belong to BPSK is decaying rapidly. This reveals that the probability that the hypothesis which doesn't belong to BPSK is chosen tends to zeros. Thus the performance of the proposed algorithm can tend to the optimal performance of QAM.

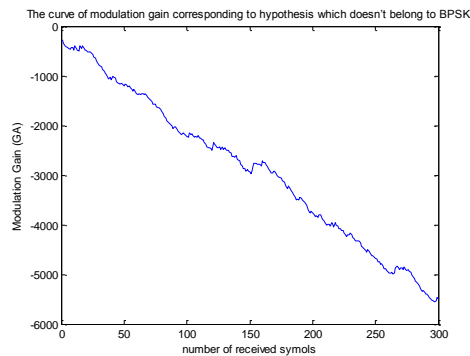


**Figure 4. The correlation curve of performance under set A and B**

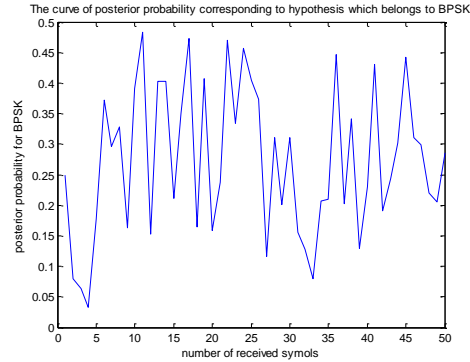


**Figure 5. The curve of modulation gain corresponding to hypothesis which belongs to BPSK**

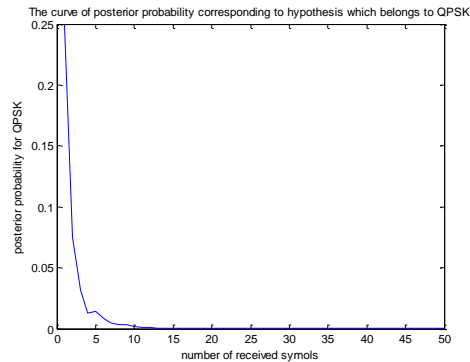
The change of posterior probability  $\Pr(M = BPSK | \bar{r}_n X)$  and  $\Pr(M = QPSK | \bar{r}_n X)$  are shown in Figures 7~8 in which  $E_s / N_0 = 1dB$  and the modulation mode is BPSK. We could find that  $\Pr(M = QPSK | \bar{r}_n X)$  tends to zero with the growth of number of iteration.



**Figure 6. The curve of modulation gain corresponding to hypothesis which doesn't belong to BPSK**



**Figure 7. The curve of posterior probability corresponding to hypothesis which belongs to BPSK**



**Figure 8. The curve of posterior probability corresponding to hypothesis which belongs to QPSK**

#### 4. Conclusion

In this paper we present a new blind demodulation algorithm based on sequential detection and an on-line receiver structure is proposed. The provided algorithm can achieve real-time output of the demodulated data, and obtains the theoretical optimal demodulation performance when the constellation is unknown. Iteration algorithm can also reduce the complexity of the receiver.

The simulation proved that with the received symbols increasing the algorithm has the asymptotical optimality. The proposed algorithm asymptotically approaches performance of QAM signal optimal demodulation method in which the constellation knowledge is known.

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