
Impaired AWGN 채널에서의 간단한 Blind 변조 신호 구분 방식

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A Simplified Blind Decision Method of Modulation Type in impaired AWGN Channel Environment

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요 약

본 논문에서는 AWGN 채널 환경에서 likelihood 함수를 사용하여 변조 신호를 구분하는 새로운 구조의 변조 신호 구분 방식을 제안한다. 제안된 방식은 각 변조 신호가 전송된다는 가정하에 likelihood 함수를 사용하지만 기존의 maximum likelihood 방식보다 더 양호한 특성을 갖는다. 기존의 maximum likelihood 방식은 구조의 복잡성과 위상 및 주파수 오프셋을 갖는 채널에서 변조 신호 구분 성능이 열화되는 특성을 갖는다. 제안된 방식은 기존 방식의 impaired 채널 환경에서의 열화 성능을 보완하는 간단한 구조의 blind 변조 구분 성능을 제공한다. 제안된 방식은 위상 및 주파수 오프셋을 갖는 채널 환경에서 기존의 maximum likelihood 방식과 성능을 모의 실험하여 비교 분석되었다. 제안된 방식의 변조 신호 구분의 정확성은 실험 결과에서 기존 방식보다 더 양호한 성능을 보였으며, 단순한 계산 방식으로 보다 더 간단한 구조를 갖는다.

ABSTRACT

In this paper, a simplified new modulation classification method that utilizes likelihood function for received signal in an impaired AWGN channel environment. The proposed method provides the superior to ML method, although the likelihood under the assumption that each modulated signal is sent utilized. On the other hand, the ML method gets the performance characteristics of high computational complexity and weakness to channel impairment such as phase offsets and frequency offsets. The proposed method has lower computational complexity than that of the ML method. Moreover, the proposed method is robust to the channel impairment such as phase offsets and frequency offsets. The correct classification probabilities of the proposed method and the ML method are given for an AWGN channel with phase offsets and frequency offsets, which were simulated with extensive Monte-Carlo simulation. As shown in simulation results, a more accurate classification performance both in phase offset environment and in frequency offset can be achieved with the low computational complexity of the proposed method.

키워드

Modulation classification, Blind decision method, Maximum-likelihood

I. Introduction

In wireless communication systems, the need for blind modulation classification at the receiver has been advent because of transmission of multiple modulation signals according to various channel circumstances, such as weather conditions in channel link. Until now, various modulation classification methods have been proposed. ML (Maximum Likelihood) methods [1]-[3] have been proposed and they have good correct classification performances, but the computational complexity leads to the methods of qLLR (quasi Log-Likelihood Ratio) [1], [4]-[6]. Moreover, the ML classification is sensitive to the model mismatches such as phase offsets and frequency offsets. Though relatively simple, the qLLR methods classify only PSK (Phase Shift Keying), and therefore these methods cannot be used to decide which QAM (Quadrature Amplitude Modulation) has been sent. In modern communication systems, MPSK (M-ary PSK) for $M \geq 16$ is hardly regarded as the pragmatic modulation scheme due to phase noise of hardware equipment and poorer BER (Bit Error Ratio) performance than QAM. In this case, QAM could be harnessed but qLLR cannot detect QAM as described above. Although Long et al. [5] proposed QAM modulation classification of a qALLR (quasi Average Log-Likelihood Ratio) test, this method is the approximation at a low SNR and it is hard to get a threshold value for general QAM modulation.

In this paper, we propose a low complexity digital modulation classification method based on the likelihood function of the received signal in the AWGN (Additive White Gaussian Noise) channel environment with phase offsets and frequency offsets. The proposed method is similar to the ML method [2], [3] in the sense that it utilizes the likelihood function of the received signal, but it has lower computational complexity than the ML method and it is less sensitive to phase offsets and frequency offsets than the ML method. This paper is organized as follows. In Section II, we give the signal model used in this paper. This section also gives a previous modulation classification method with this signal model. Section III provides the new modulation classification method based on the ML method. In Section IV, we give

some numerical simulation results and discussion to verify the performance of the proposed method and the conclusions are represented in the Section V.

II. Signal Model and Preliminary Results

In the AWGN channel environment, the matched-filtered received signal at the k -th ($1 \leq k \leq N$) time instant can be modeled as

$$r_k = s_k e^{j(2\pi k F_o T_s + \Theta_k)} + n_k \quad (1)$$

where s_k is the transmitted symbol and n_k is the additive white Gaussian noise with two-sided power spectral density of $N_o/2$. F_o is the residual frequency offset, Θ_k is the phase offset, and T_s is the symbol duration. Let Ω be the set of modulation alphabets which should be classified. In this paper, we let $\Omega = \{\text{BPSK}, \text{QPSK}, \text{16QAM}\}$. Under the assumption that $\Theta_{M_i} \in \Omega$ modulated signal is transmitted, the likelihood function of the received signal is

$$p(r_k | \Theta_{M_i}) \equiv \sum_{i=1}^{M_j} \frac{1}{M_j} e^{-\frac{|r_k - x_i|^2}{N_o/2}} \quad (2)$$

where $x_{i,j} \in \Theta_{M_i}$ is the modulation symbol and M_j is the number of elements in the set Θ_{M_i} , i.e. $M_j = |\Theta_{M_i}|$.

where $|\cdot|$ denotes the number of elements in a set (\cdot). Here we assumed that the modulation symbols are equally probable. With N received samples being observed, the joint likelihood function of r_1, r_2, \dots, r_N under the assumption that Θ_{M_i} -modulated signal is sent is given by

$$p(r | \Theta_{M_i}) \equiv \prod_{k=1}^N \sum_{i=1}^{M_j} \frac{1}{M_j} e^{-\frac{|r_k - x_i|^2}{N_o/2}} \quad (3)$$

where $r = [r_1, r_2, \dots, r_N]^T$. Assume that s_k 's are mutually independent. The log-likelihood function is defined by

$$f(r|\Theta_{M_j}) \equiv \ln p(r|\Theta_{M_j}) = \sum_{k=1}^N \ln \left(\sum_{i=1}^{M_j} \frac{1}{M_j} e^{-\frac{|r_k - x_{ij}|^2}{N_0/2}} \right). \quad (4)$$

The decision rule which be found in [2],[3] is given by

$$\Theta_M = \arg \max_{\Theta_{M_j}} f(r|\Theta_{M_j}). \quad (5)$$

III. Proposed Classification Method

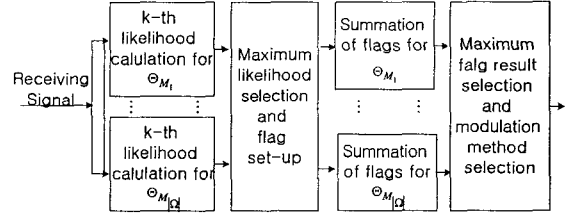
In this section, we will propose a new modulation classification method based on (4). With the inequality of $\ln x \leq x$ for $x > 0$, (4) can be simplified by

$$f(r|\Theta_{M_j}) \leq \sum_{k=1}^N \sum_{i=1}^{M_j} \frac{1}{M_j} e^{-\frac{|r_k - x_{ij}|^2}{N_0/2}} \quad (6)$$

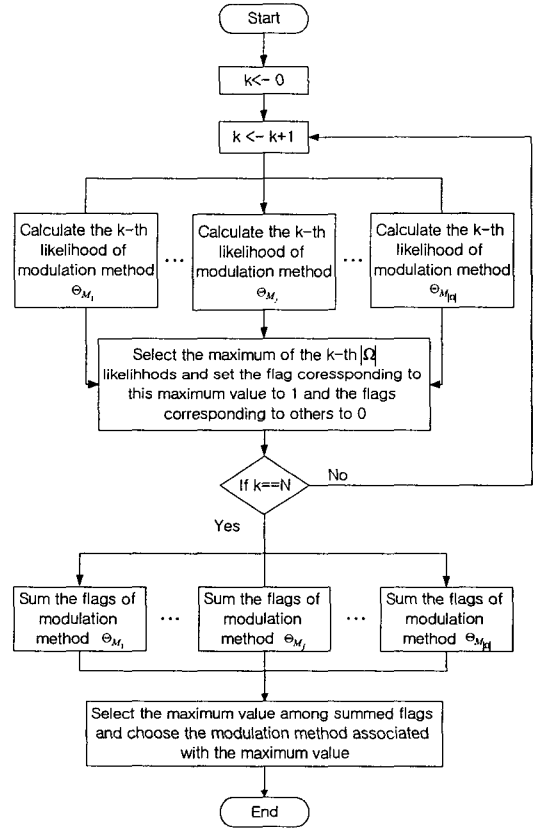
We can further progress in simplification of the above equation by selecting maximum value among $\sum_{i=1}^{M_j} \frac{1}{M_j} e^{-\frac{|r_k - x_{ij}|^2}{N_0/2}}$, $j = 1, \dots, |\Omega|$ and setting the flag corresponding to this maximum value to 1 and the flags corresponding to the others to 0. Let X_{jk} denote this flag. Then the decision rule is given by

$$\Theta_M = \arg \max_{\Theta_{M_j}} \sum_{k=1}^N X_{jk}. \quad (7)$$

Fig. 1 is the conceptual block diagram and flowchart that summarizes the proposed method. The advantages of the proposed method compared to the ML method can be explained as follows: the ML method uses a log function to calculate the likelihood ratio at each step and sums the calculated log values for all N steps, but the proposed method reduces the computational complexity by a hard decision of each likelihood without calculation of a log function and by counting of only nonzero X_{jk} for $1 \leq j \leq N$ determined by the hard decision. Moreover, the ML method accumulates the



(a)



(b)

Fig. 1. The conceptual block diagram (a) and flowchart (b) of proposed method.

numerical errors by considering all N consecutive symbols, but the proposed method is considered to have numerically small errors by not aggregating the consecutive numerical errors and limiting the errors at each step. Besides, while the ML method accumulates effects of phase offsets and frequency offsets by summing the effects of N consecutive

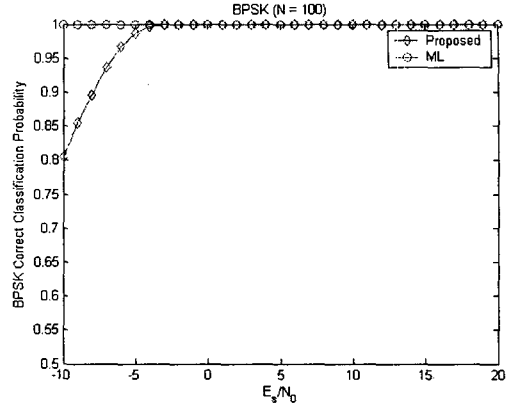
symbols, the proposed method makes an independent decision for each step and therefore limits effects of phase offsets and frequency offsets to each step. Therefore, the proposed method can be robust to channel mismatches such as phase offsets and frequency offsets. We will show these phenomena with simulation results in the next section.

IV. Simulation Results and Discussion

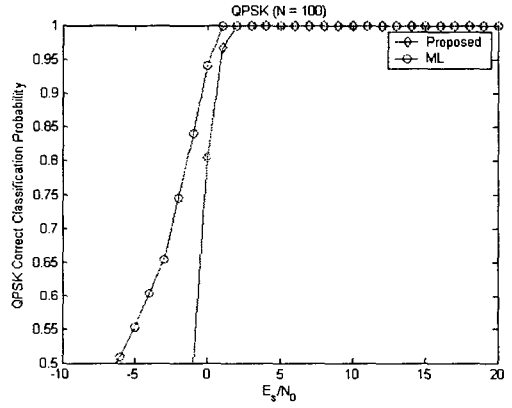
In this section, we provide simulation results of the proposed method and the ML method. As simulation environment in this paper, AWGN channel with phase offsets and frequency offsets is assumed. We observed $N=100$ symbols to provide the correct classification probabilities of the proposed method and the ML method, and iterated 15000 for each modulation scheme. In this simulation, we use phases of PSK-modulated signals as following: $\angle(BPSK) = \{0, \pi\}$, $\angle(QPSK) = \{\pi/4, 3\pi/4, 5\pi/4, 7\pi/4\}$, where $\angle(\cdot)$ is defined by a set of phases of a set (\cdot) . The average energy per symbol(E_s) of all PSK- and QAM-modulated signals were set to 1.

Fig. 2 shows the performances of the proposed method and ML method in conditions of ideal channel environment, which means channel status with no phase and frequency offset. In this case the correct modulation classification probabilities of ML method are superior to those of the proposed method. Though the ML method provides the good performances in low signal-to-noise ratio, the proposed method shows the good performances above a proper signal-to-noise ratio, which may be a actual communication environment. The proposed method, however, provides the predominant performance over the ML method in the impaired AWGN channel, such as channel with the phase and frequency offsets.

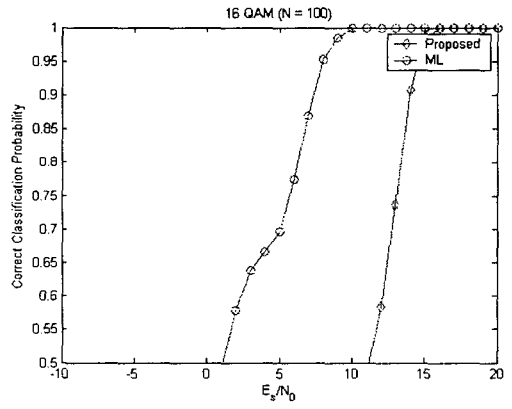
Fig. 3 shows the correct classification probabilities of the proposed method and the ML method when the phase offsets exist. The frequency offsets were set to be zero. The phase offsets were generated such that the phase offsets were uniformly distributed over $[-\Theta, \Theta]$, where Θ denotes



(a)

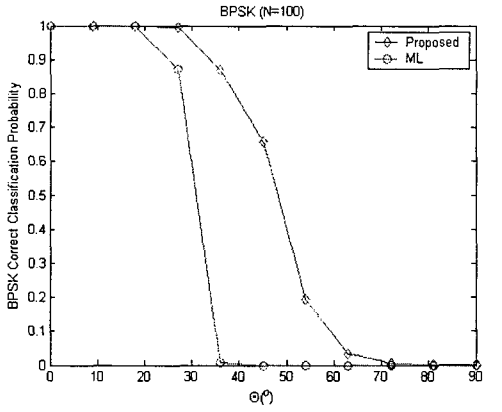


(b)

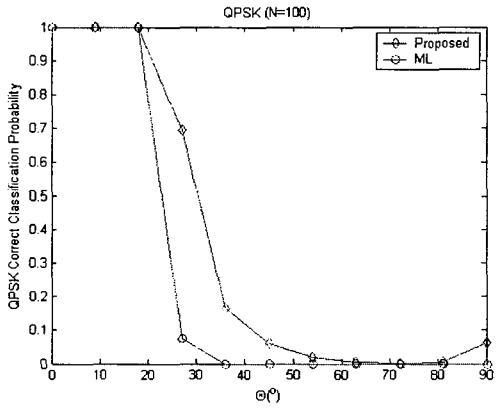


(c)

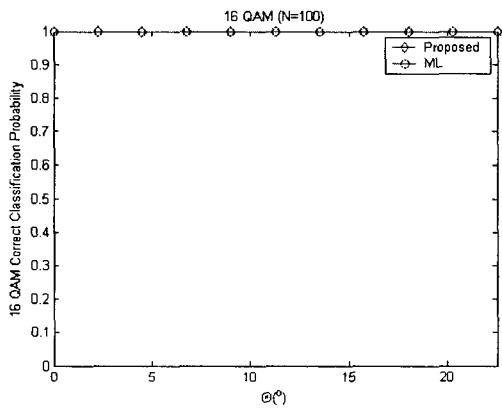
Fig. 2. Correct classification probabilities for proposed method and ML method in condition of ideal channel environment, (a) BPSK, (b) QPSK and (c) 16 QAM.



(a)

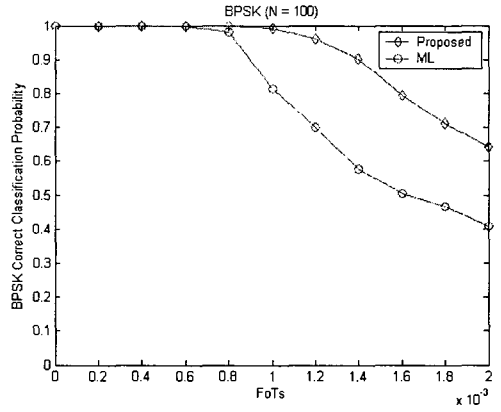


(b)

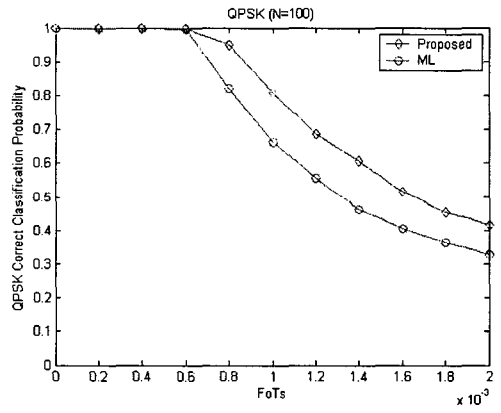


(c)

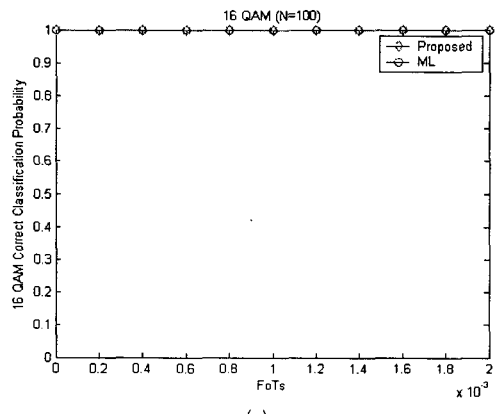
Fig. 3. Correct classification probabilities for proposed method and ML method in condition of phase offset environment, (a) BPSK, (b) QPSK and (c) 16 QAM.



(a)



(b)



(c)

Fig. 4. Correct classification probabilities for proposed method and ML method in condition of frequency offset environment, (a) BPSK, (b) QPSK and (c) 16 QAM.

the angle at the x-axis of Fig. 3 in degrees. In this simulation, we set $E_s/N_0 = 10$ dB and 15 dB for BPSK, QPSK and 16 QAM, respectively. This figure shows that the proposed method is robust to the phase offsets compared to the ML method. Also, Fig. 4 shows the correct classification probabilities of the proposed method and the ML method when the frequency offsets exist.

and the phase offsets were set to be zero. The frequency offsets were generated such that the frequency offsets were uniformly distributed over $[-F_oT_s, F_oT_s]$, where F_oT_s denotes the normalized frequency offset at the x-axis of Fig. 4. In this simulation, we also set $E_s/N_0 = 10$ dB and 15 dB for BPSK, QPSK and 16 QAM, respectively. This figure also shows that the proposed method is robust to the frequency offsets compared to the ML method. In the above simulation results, we see that the proposed method has better correct classification performance than the ML method in the impaired AWGN channel environment. From these results, due to imperfect recovery of frequency and phase of communication equipment in real communication systems, the direct use of ML method is not appropriate and the proposed method works well in the real communication channel.

V. Conclusions

We proposed a low complexity modulation classification method using the likelihood of the received signal. Compared to the ML method, the proposed method reduces the computational complexity and it is numerically stable. Moreover, although it has worse performance than the ML method in no phase offset and no frequency offset channel environment, the proposed method reduces the effects of phase offsets and frequency offsets. In flat fading channel environment, if we know the fading channel coefficient, our result can readily be extended, and therefore in OFDM (Orthogonal Frequency Division Multiplexing) systems, per each tone signal, it can be used in blind adaptive modulation classification system

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