Computers and Electrical Engineering 56 (2016) 85–95

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Data-classification-based SNR estimation for linearly modulated signals ☆

Taleb Moazzeni [a,*], Yingtao Jiang [a], Tian-Ding Chen [b]

[a] Department of Electrical and Computer Engineering, University of Nevada Las Vegas, Las Vegas, NV 89154, USA
[b] Department of Information and Electronics Engineering, Zhejiang Gongshang University, Hangzhou, Zhejiang, People's Republic of China

ARTICLE INFO

Article history:
Received 3 April 2016
Revised 5 September 2016
Accepted 16 September 2016

Keywords:
Signal to noise ratio
Digital modulation
AWGN channels
Data classification
Quantile classification

ABSTRACT

We present a new numerical approach to SNR estimation of linearly modulated signals after passing through a complex additive white Gaussian noise (AWGN) channel. This classified data (CD) based SNR estimator is particularly suitable for both constant and non-constant modulus constellations, including BPSK, M-PSK and M-QAM. In essence, the received data will be first classified into a number of classes, and then a look-up table (LUT) is searched to find an entry that closest matches with the classified data; this matched result in LUT corresponds to the SNR value of the received data. The performance of the proposed estimator in terms of accuracy and complexity is evaluated by numerical simulations and compared with a few well-known estimators such as moment and maximum likelihood based estimators.

1. Introduction

Many of existing and emerging communications systems require SNR information for the purposes of power control, adaptive coding and modulation, and/or soft decoding [1–6]. A number of SNR estimation techniques thus have been introduced in the literature which can be categorized into two main classes [7]: the maximum likelihood- (ML) and the moments-based estimators. The performance of the moments-based estimators is close to the Cramer-Rao Lower Bound (CRLB) for constant modulus constellations [8,9], while for multilevel constellations [10,11], CRLB performance of these moments-based SNR estimators worsens as SNR increases [8,9,12]. On the other hand, the ML-based estimators [13–15] give favorable results in terms of accuracy and they are shown to be asymptotically optimal with minimum variance [16], but they tend to be computationally expensive [17,18].

In [19], it was suggested that the order statistics can help build quick and simple, but yet highly efficient estimators. This concept is certainly applicable to the construction of an SNR estimator; to our best knowledge, no effort though has been made to do so. In [20], we introduced an ordered-data-based technique to estimate SNR for BPSK signals only. This technique can actually be generalized to estimate SNR for any constellation, including M-PSK and M-QAM. In the proposed technique, in this paper, we use data classification instead of order statistics [21] as used in [20].

In contrast to the current SNR estimators, this proposed approach scales well as the modulation array increases. From the computation perspective, due to its computational simplicity, our proposed estimation approach holds the potential to

☆ This paper is for regular issues of CAEE. Reviews processed and recommended for publication to the Editor-in-Chief by Associate Editor Dr. Z. Arnavut.

* Corresponding author.
E-mail addresses: taleb.moazzeni@gmail.com (T. Moazzeni), yingtao.jiang@unlv.edu (Y. Jiang), yingtao99@hotmail.com (T.-D. Chen).

http://dx.doi.org/10.1016/j.compeleceng.2016.09.017
0045-7906/

work for any modulation scheme and channel model, provided such information is known to the receiver. In this paper, our attention is focused on (quasi) static flat fading channel with complex additive white Gaussian noise (AWGN).

The rest of this paper is organized as follows. In Section 2, the signal model is described. The problem of SNR estimation for BPSK, M-PSK and M-QAM constellations is also formulated in this section. Section 3 presents some existing SNR estimation method with problem formulation. Section 4 introduces the proposed SNR estimation method. Section 5 describes a classification method that is needed for the proposed SNR estimator. Section 6 discusses the look-up table generation and shows how the SNR estimator can be built with the classified data using such a look-up table. The proposed SNR estimator is compared with a number of known estimators, and the results are reported in Section 7. Finally, conclusions are drawn in Section 8.

2. Signal model

Assume that the receiver can recover the transmitted signal due to perfect synchronization. In specific, the received signal at the output of the matched filter is a complex signal modeled as,

$$y(n) = Sa(n)e^{j\varphi} + w(n) \quad n = 1, 2, \ldots, N, \tag{1}$$

$$a(n) = a_I(n) + ja_Q(n) \tag{2}$$

$$w(n) = w_I(n) + jw_Q(n) \tag{3}$$

where at time index n, $y(n)$ is the observation, S is the amplitude of the transmitted symbol, $a(n)$ is the original symbol with unit energy, i.e., $E\{|a(n)|^2\} = 1$, φ is the channel phase and $w(n)$ is the noise. The subscripts I and Q, respectively, denote the real and imaginary parts, or the in-phase and quadrature components. N is the number of samples during the observation interval. The noise component is modeled by a zero-mean Gaussian random variable with independent real and imaginary parts, each of which has a variance of σ^2. We assume that the transmitted symbols are independent and identically distributed and drawn from either an M-ary PSK or a square QAM constellation. Also, we assume that the channel is memoryless and slowly time-varying so that it can be adequately modeled over the observation interval by a constant real gain S and a phase φ that accounts for any constant phase distortion introduced by the channel [22]. This assumption is very crucial for the performance of the proposed method as the estimator uses constant data in the look-up table obtained from a constant gain channel. It is expected that the performance of the proposed SNR estimator is drastically degraded if the channel gain varies with time. In other words, this works only under the assumption that the channel remains approximately constant during the estimation.

For the N received samples, the SNR of interest is defined as [23],

$$\rho = \frac{S^2}{2\sigma^2} \tag{4}$$

Note that in the case of BPSK constellation, the imaginary parts defined in (2) and (3) are zero, $a(n)$'s are the symbols taking the values of ± 1 with equal probabilities to be 1 or -1; in this case, the SNR is defined by,

$$\rho = \frac{S^2}{\sigma^2} \tag{5}$$

3. Existing SNR estimation methods

For comparison of the performance of the proposed SNR estimator with existing estimators, we consider three estimation methods: ML-based estimator [16], the squared signal to noise variance estimator with data-aided using an estimate of the transmitted data sequence from receiver (SNV RxDA) [8] and the well-known M_2M_4 [8] estimator. There are theoretical models for these estimators in the literatures and they can be written compactly as [8,16],

$$\hat{\rho}_{\text{SNVRxDA}} = \frac{\left[\frac{1}{N}\sum_{n=1}^{N} \text{Re}\left\{y*(n)a^{(\hat{i})}(n)\right\}\right]^2}{\frac{1}{N-K_a}\sum_{n=1}^{N}|y(n)|^2 - \frac{1}{N(N-K_a)}\left[\sum_{n=1}^{N}\text{Re}\left\{y*(n)a^{(\hat{i})}(n)\right\}\right]^2} \tag{6}$$

where Re denotes the real part, i denotes the i-th sequence of M^N possible sequences in the M-ary modulated signal, $\hat{i}$ represents the sequence of symbols estimated by the receiver, *denotes complex conjugation, $K_a = 1$ for the real BPSK data, and $K_a = 3/2$ for the complex PSK and QAM data.

$$\hat{\rho}_{\text{M}_2\text{M}_4} = \frac{\sqrt{2{M_2}^2 - M_4}}{M_2 - \sqrt{2{M_2}^2 - M_4}} \tag{7}$$

where M_2 and M_4 are the second and fourth moments of $y(n)$ given by,

$$M_2 \approx \frac{1}{N}\sum_{n=1}^{N}|y(n)|^2 \tag{8}$$