A Highly Accurate and Low Bias SNR Estimator: Algorithm and Implementation

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Abstract. *Signal to noise ratio (SNR) estimators are required for many radio engineering applications. In this paper, a SNR estimator based on the first and second order moments is derived and examined for constant envelope modulations over additive white Gaussian noise (AWGN) channel. Firstly, a modification method is proposed to reduce the bias of conventional first and second order moments based SNR estimator. Then, in order to reduce hardware implementation complexity, multi segments of cubic polynomial are utilized to approximate the nonlinear inverse function of the proposed SNR estimator. The approximate expression is very precise in the SNR range from -10dB to 20 dB as illustrated by numerical simulation results. Besides, practical hardware circuit is proposed for FPGA implementation. Simulation results show that the proposed SNR estimator has the lower normalized bias and variance when compared with two other classic estimators.*

Keywords

SNR estimation, MPSK, moment based, curve fitting, FPGA.

1. Introduction

Many radio engineering applications require highly accurate and low bias estimation of signal to noise ratio (SNR) to achieve optimal performance. For example, in modem wireless communication networks, the coding and modulation methods of the transmitted data stream are adapted to match the channel capacity according to the SNR of the channel [1]. Besides, the knowledge of SNR is very important to the iterative decoding and detection techniques which represent the state of the art in wireless digital receiver technology [2]. SNR estimation is also often a requirement for many other applications such as power control, equalization, handoff and dynamic allocation of resources [3].

Various works cited in the literature are devoted to the estimation of SNR using data-aided (DA) or non-data-aided (NDA) approaches. Special pilot symbols or training sequence known to the receiver must be inserted into the data stream for the DA estimators, which reduce the system throughput. Considering the bandwidth efficiency, the NDA estimators may be more favorable choice for many applications. Hence, we only study the NDA SNR estimation techniques in this paper. Roughly speaking, the NDA estimators can be further divided into two major categories, the carrier aided (CA) and non-carrier aided (NCA) methods, depending on whether the carrier parameters, frequency and init-phase, are prior known or not. For the CA method, several estimators have been investigated. In [4], the authors introduced an online SNR estimator with SNR in the range from 0 to 6 dB which was broadened to -5 ~ 12 in [5]. Besides, four simple estimators for QPSK modulation were compared in [6]. In order to reduce the bias in the low SNR, the authors proposed an iterative estimation approach in [7] at the expense of higher complexity. In [8], a simple SNR estimator was proposed for QPSK modulation. However, all of the above mentioned CA estimators are sensitive to carrier parameter estimation errors. In order to avoid the problem, SNR can also be estimated based on envelope of the received signals which is NCA method. As the signal envelope is independent of the carrier frequency and phase, the carrier parameter estimation errors have no influence on the NCA estimators. The algorithm utilizing the second and fourth order moments of envelope, referred to as M2M4 [9], [10], may be the most famous NCA estimator. In [11], the authors proposed a highly accurate NCA estimator using the first and second order moments, which can be implement by a lookup table. The drawback of the algorithm is that the bias tends to increase with the SNR due to the finite dimension of the lookup table. An iterative estimation technique was derived in [12], which avoid the finite accurate problem in [11]. Besides, envelope based SNR estimators were extended for APSK and QAM modulation in [13] and [14] respectively.

In this paper, we focus on design NCA SNR estimator for *M*-ary phase shift keying (MPSK) modulation over AWGN channel. The proposed estimator achieves highly accurate and low bias in a wide SNR range as proved by simulation and it is also very suitable for hardware implementation on field programmable gate array (FPGA).

The remainder of this paper is organized as follow. First of all, we introduce the system model and some basic concept in section 2. Then a new SNR estimator is derived in section 3. What's more, we use multi-segments of cubic polynomial to approximate the expression of the new estimator and present a practical hardware circuit in section 4. In section 5, the performances of the proposed estimator are evaluated and compared with other two classic SNR estimators by numerical simulation. Finally, section 6 concludes the paper.

2. System Model

We consider the MPSK modulation over an AWGN channel. Assuming perfect timing synchronization has been realized, the received symbol-spaced samples at the matched filter output can be represented by

$$r_n = Ae^{j(2\pi fnT+\theta+2\pi c_n/M)} + \omega_n \tag{1}$$

where $n = 0,1,2\cdots N-1$ is the time index in the observation interval, A is the amplitude of the transmitted signal, f and θ are the carrier frequency and init-phase respectively, T is the symbol space, M is the modulation order, $c_n \in (0,1,2,\cdots M-1)$ is the modulating data and ω_n is a complex white Gaussian random variable having zero mean and variance $2\sigma^2$. The SNR of the received samples is defined as the ratio of transmitted signal power S to the one side noise power spectral density N_0, which can be given by

$$\rho = \frac{S}{N_0} = \frac{A^2}{2\sigma^2} \tag{2}$$

What we are interested in is the signal envelope which is defined as

$$u_n = |r_n| \tag{3}$$

where $|\cdot|$ denotes absolute value. It's obvious that u_n has no relationship with the phase of the received samples. Hence, the carrier parameter estimation results have no influence on envelope based estimators, and the estimator can be used for MPSK modulation with any value of M. As pointed out in [15], the envelope u_n is Ricean distributed and the k th order moment of u_n can be expressed as

$$M_k = E[u_n^k] = (\sigma^2)^{k/2}\Gamma(k/2+1)e^{-\rho}{}_1F_1(k/2+1;1;\rho) \tag{4}$$

where $E[.]$ denotes expectation, $\Gamma(.)$ is the gamma function, and ${}_1F_1(\cdot;\cdot;\cdot)$ is the confluent hyper geometric function. It's not difficult to find from (4) that the k th moment of u_n depends only on two unknown parameters σ^2 and ρ. Hence the value of ρ can be estimated utilizing at least two different moments.

3. Estimation Algorithm

Our goal is to find a highly accurate and low bias SNR estimator with the least hardware cost and without the knowledge of carrier parameters. Suppose that k is not equal to l, we can get the following equation [11]

$$\lambda_{k,l} = \frac{M_k^l}{M_l^k} = f_{k,l}(\rho) = \frac{(\Gamma(k/2+1)e^{-\rho}{}_1F_1(k/2+1;1;\rho))^l}{(\Gamma(l/2+1)e^{-\rho}{}_1F_1(l/2+1;1;\rho))^k} \tag{5}$$

which depends only on ρ but not on σ^2. As $f_{k,l}$ is a monotone function in the interval $\rho \in (0,+\infty)$, the envelope based estimator that depends on the k th and l th order moment can be got by inverting the corresponding $f_{k,l}$ to solve for ρ, which can be expressed as

$$\rho = f_{k,l}^{-1}\left(\frac{M_k^l}{M_l^k}\right). \tag{6}$$

This is a unified expression for all kinds of envelope based SNR estimators.

3.1 Conventional Envelope Based Algorithms

Although the moment orders can be any two different values for equation (6), only the second and fourth order moments based estimator (M2M4) has a close form solution as we know. The M2M4 algorithm can be expressed as

$$\rho_{2,4} = \frac{-2\lambda_{2,4}+1-\sqrt{2\lambda_{2,4}^2-\lambda_{2,4}}}{\lambda_{2,4}-1}. \tag{7}$$

In fact, it's the equivalent to the algorithm proposed in [6].

For MPSK modulation, the optimum choice for k and l are $k=1$ and $l=2$ as demonstrated by simulation result in [11]. The expression of the first and second moments based estimator is given by

$$\rho_{1,2} = f_{1,2}^{-1}(\lambda_{1,2}), \tag{8}$$

$$\lambda_{1,2} = f_{1,2}(\rho) = \frac{\pi e^{-\rho}}{4(1+\rho)}((1+\rho)I_0(\frac{\rho}{2})+\rho I_1(\frac{\rho}{2}))^2. \tag{9}$$

where $\lambda_{1,2} = M_1^2/M_2$, and $I_m(\cdot)$ is Bessel function of the first kind with the order m. Although it's not a close form solution for $\rho_{1,2}$, it can be realized by a lookup table which would simple consist of a number of samples of the inverse function $f^{1}{}_{1,2}(\cdot)$. As an alternative, the authors proposed an iterative estimation algorithm which was also based on the first and second moments in [12]. The iterative estimator uses a simplified equation to estimate the SNR in the first, and then iteratively revises the bias step by step. The detail about the iterative process can be found in [12]. As shown by simulation result in [12], the performance of the two implementation method is similar to each other. Hence we refer to both of the two algorithms as M1M2 in simulation.

In practice, the first, second and fourth order moments are estimated by their respective time averages as

$$\hat{\lambda}_{2,4} = \frac{\hat{M}_2^2}{\hat{M}_4} = \frac{(\frac{1}{N}\sum_{n=0}^{N-1}u_n^2)^2}{\frac{1}{N}\sum_{n=0}^{N-1}u_n^4}, \tag{10}$$

$$\hat{\lambda}_{1,2} = \frac{\hat{M}_1^2}{\hat{M}_2} = \frac{(\frac{1}{N}\sum_{n=0}^{N-1} u_n)^2}{\frac{1}{N}\sum_{n=0}^{N-1} u_n^2} \tag{11}$$

where N is the observation length. As u_n is known in the receiver, the SNR of the received samples can be estimated utilizing above two statistics with equation (7) and (8).

3.2 New Algorithm

All of above mentioned algorithms use these statistics to replace corresponding parameters directly. However, we find that there is bias for the M1M2 estimator especially when the observation length is short. Let's evaluate the expectation of $\hat{M}_1^2$, which can be expressed as

$$\begin{aligned} E[\hat{M}_1^2] &= E[(\frac{1}{N}\sum_{n=0}^{N-1} u_n)^2] \\ &= E[\frac{1}{N^2}\sum_{n=0}^{N-1} u_n^2] + E[\frac{1}{N^2}\sum_{n=0}^{N-1}\sum_{m=0;m\neq n}^{N-1} u_n u_m] \end{aligned} \tag{12}$$

If n is not equal to m, u_n is independent of u_m. So we can further express (11) as

$$\begin{aligned} E[\hat{M}_1^2] &= \frac{1}{N^2}\sum_{n=0}^{N-1} E[u_n^2] + \frac{1}{N^2}\sum_{n=0}^{N-1}\sum_{m=0;m\neq n}^{N-1} E[u_n]E[u_m] \\ &= \frac{1}{N}M_2 + \frac{N-1}{N}M_1^2 \end{aligned} \tag{13}$$

Ignoring the effect of the divider in (10), the expectation of the statistic $\hat{\lambda}_{1,2}$ can be expressed using (11) and (12) as

$$E[\hat{\lambda}_{1,2}] \approx \frac{1}{N} + \frac{N-1}{N}\frac{M_1^2}{M_2} = \frac{1}{N} + \frac{N-1}{N}\lambda_{1,2}\,. \tag{14}$$

Above equation indicates that $\hat{\lambda}_{1,2}$ is a biased estimation of $\lambda_{1,2}$. What's more, we can reduce the bias by

$$\tilde{\lambda}_{1,2} = \frac{N}{N-1}\hat{\lambda}_{1,2} - \frac{1}{N-1}\ . \tag{15}$$

The effect of the proposed modification method with $N = 32$ is illustrated by Fig. 1. We can see that there is an obvious gap between $\hat{\lambda}_{1,2}$ and $\lambda_{1,2}$, whereas the modified statistic $\tilde{\lambda}_{1,2}$ tightly match to the real value of $\lambda_{1,2}$. The corresponding SNR range is from -10 dB to 20 dB.

Although the modification method given by (15) does reduce the estimation bias as proved by simulation results, we find that the estimation of ρ utilizing $\tilde{\lambda}_{1,2}$ is still biased. That's because the inverse function $f^{1}{}_{1,2}(\cdot)$ is nonlinear which induces that an unbiased estimation of $\lambda_{1,2}$ can't ensure unbiased estimation of ρ. Motivated by the improvement of (15), we hope that residual bias can be further reduced if the result of (15) is modified in the same way once again. Hence an ad hoc modification method is given by

$$\tilde{\lambda}_{1,2}^{'} = \frac{N}{N-1}\tilde{\lambda}_{1,2} - \frac{1}{N-1} = \frac{N^2}{(N-1)^2}\hat{\lambda}_{1,2} + \frac{1-2N}{(N-1)^2}\,. \tag{16}$$

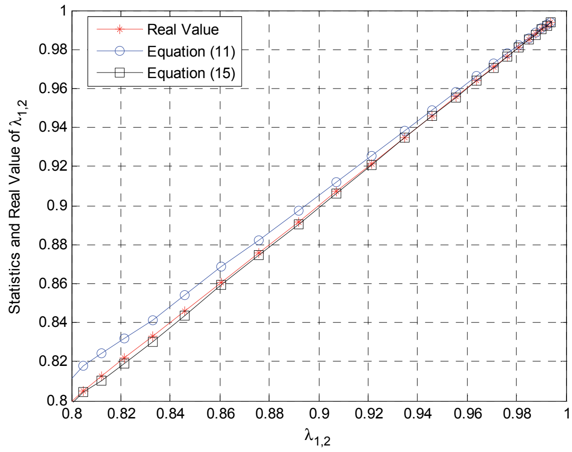

Fig. 1. Statistics vs. real value of $\lambda_{1,2}$.

Finally, the new algorithms can be expressed as

$$\hat{\rho}_{new1} = f_{1,2}^{-1}(\tilde{\lambda}_{1,2})\,, \tag{17}$$

$$\hat{\rho}_{new2} = f_{1,2}^{-1}(\tilde{\lambda}_{1,2}^{'}) \tag{18}$$

which are referred to as Modify1 and Modify2 respectively in the following discussion.

4. Hardware Implementation

We are interested in implementing the SNR estimator on the FPGA. As the main difficulty for hardware implementation is how to realize the inverse function $f^{-1}{}_{1,2}(\cdot)$, we focus on the realization methods of the inverse function. Although there is no precise close form solution for the inverse function, it can be realized by lookup table, iterative processing or curve fitting methods. The lookup table technique may be the simplest method, but the table will become too big to be implemented on the FPGA when wide range of SNR and high accuracy are required. The iterative processing technique is also not suitable for hardware implementation, since it requires many nonlinear computations which will use too much hardware resources. Hence, we choose the curve fitting technique.

The basic idea of curve fitting is using polynomials to approximate a nonlinear curve. In [4], a second order polynomial is used to approximate the inverse function of a CA SNR estimator in the SNR range from 0 to 6 dB. The SNR range is broadened to -5~12dB utilizing a fifth order polynomial in [5]. After thorough research, we find that the second order polynomial can't approximate the curve with high precise over a large range of SNR and the fifth order polynomial requires too much hardware resources, although the second order polynomial and fifth order polynomial can also be used for the NCA SNR estimator. A superior method is using multi-segments of cubic (third order) polynomial. In order to reduce the bits used for representing the polynomial parameters, we rewrite equation (8) in the decibel domain as

$$\rho_{dB} = 10\log_{10}(f_{1,2}^{-1}(10^{\lambda_{dB}/10})) = g(\lambda_{dB}) \qquad (19)$$

where $\lambda_{dB} = 10\log 10(\lambda_{1,2})$ and $\rho_{dB} = 10\log 10(\rho_{1,2})$. Besides, the expression of (9) in the decibel domain can be given by

$$\lambda_{dB} = 10\log_{10} f_{1,2}(10^{\rho_{dB}/10}). \qquad (20)$$

As (20) is close form, we can calculate λ_{dB} if ρ_{dB} is know. This mapping is one to one and (19) is the inverse of (20), so we can get a group of data about (19). Using the MATLAB function 'POLYFIT' to fit these data, we can achieve the approximate expression of (19) by multi-segments of cubic polynomial as

$$\rho_{dB}^{'} = (a_s\lambda_{dB}^3 + b_s\lambda_{dB}^2 + c_s\lambda_{dB} + d_s)/2^3 \qquad (21)$$

where s is the index of segment. The value of s is decided by

$$s = \begin{cases} 1 & \lambda_{dB} \le \text{-}1.0120 \\ 2 & \text{-}1.0120 < \lambda_{dB} \le \text{-}0.8531 \\ 3 & \text{-}0.8531 < \lambda_{dB} \le \text{-}0.1966 \\ 4 & \text{-}0.1966 < \lambda_{dB} \le \text{-}0.0665 \\ 5 & \text{-}0.0665 < \lambda_{dB} \le \text{-}0.0215 \end{cases} \qquad (22)$$

and the polynomial parameters for different segment and corresponding SNR range are giving in Tab. 1.

s	a_s	b_s	c_s	d_s	SNR range (dB)
1	1440135	4409935	4501934	1532113	-10<SNR≤ -5
2	4779	12488	11038	3295	-5<SNR≤ 0
3	190	324	285	125	0<SNR≤ 10
4	9714	4787	1033	170	10<SNR≤ 15
5	272967	44429	3117	209	15<SNR≤ 20

Tab. 1. Polynomial parameters for different segments.

The strobe of λ_{dB} is optimized based on many trails. We can find from Tab. 1 that 9 bits are enough to represent the parameters if we are only interested in the SNR range 0~10 dB. 15 bits will be required if the range is broadened to -5~15 dB. 21 bits will be required when the range of SNR is from -10 dB to 20 dB. The curve fitting effect can be seen from Fig. 2. It is obvious that the two curves match to each other perfectly.

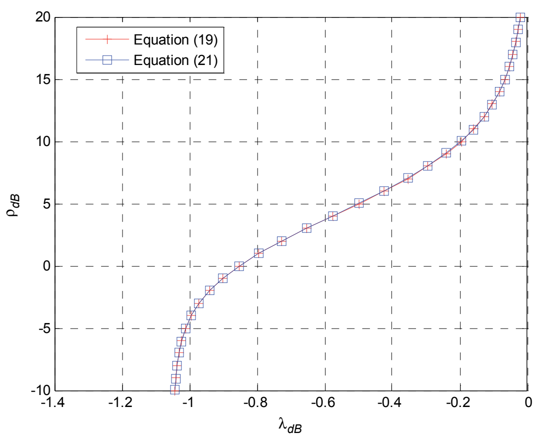

Fig. 2. Curve fitting effect.

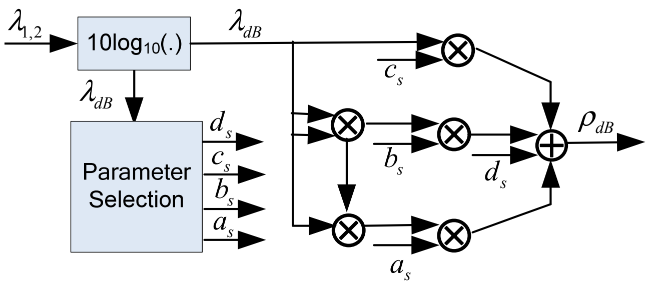

Fig. 3. Hardware circuit of the inverse function in the decibel domain.

The hardware circuit of the inverse function in decibel domain for FPGA implementation is given in Fig. 3. The logarithm conversion can be implemented by a low complexity technique named Coordinate Rotation Digital Computer (CORDIC) [16]. The polynomial parameters of all segments are stored in a small table and selected by the input statistic according to (22). It should be point out that the input of the circuit can be $\hat{\lambda}_{1,2}$, $\tilde{\lambda}_{1,2}$ or $\tilde{\lambda}_{1,2}^{'}$ which refer to different algorithms.

5. Numerical Simulation

The 'best' SNR estimator is the one that is unbiased (or exhibits the smallest bias) and has the smallest variance [3]. Hence, we evaluate the normalized bias (NB) and normalized mean square error (NMSE) of the proposed estimator by numerical simulation. The bias and mean square error normalized to the true SNR are computed from L trials respectively as

$$\text{NB}(\hat{\rho}) = \frac{1}{L}\sum_{l=1}^{L}\frac{\hat{\rho}_l - \rho}{\rho}, \qquad (23)$$

$$\text{NMSE}(\hat{\rho}) = \frac{1}{L}\sum_{l=1}^{L}(\frac{\hat{\rho}_l - \rho}{\rho})^2 \qquad (24)$$

where $\hat{\rho}_l$ is the estimation of ρ at the l th trial.

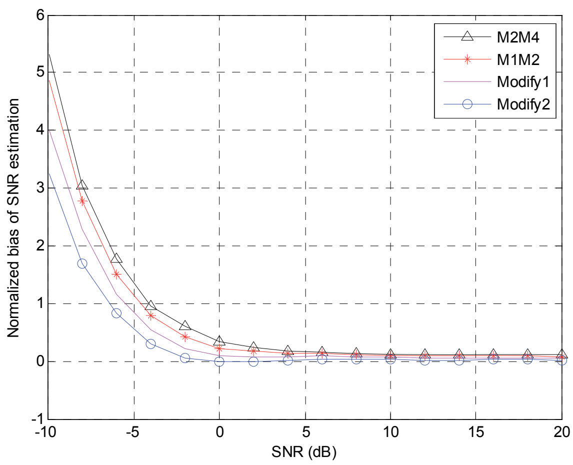

Fig. 4. Normalized biases of several SNR estimators.

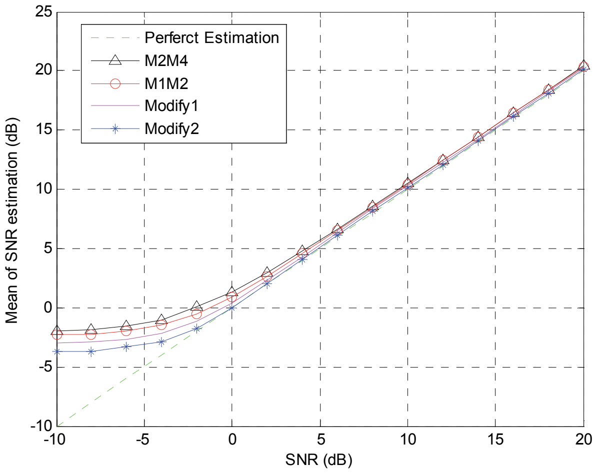

Fig. 5. Mean values of several SNR estimators.

For comparison, simulation results are also provided for the conventional M2M4 and M1M2 algorithms. $L = 10000$ trials are made and observation length for each trial is $N = 32$ in simulation. The received samples are QPSK modulated. The normalized frequency and init-phase are set to be $fT = 0.01$ and $\theta = 0.2$ respectively without loss of generality.

Fig. 4 shows the normalized bias of the estimators as function of SNR over the range from -10 dB to 20 dB. We can see that the proposed SNR estimator, Modify2, performs best over the whole range of SNR. The bias of Modify1 is lower than the M2M4 and M1M2, but is higher than the Modify2. Although someone may think that the bias can be further reduced if the statistic $\tilde{\lambda}'_{1,2}$ modified one more time, we find it's not true by simulation. Proof of the result with theoretical analyses may be a further work which is intractable and not presented here. The performance gain of the Modify2 increases with the decrease of SNR. That's because the influence of the additive modify factor $(1 - 2N)/(N - 1)^2$ in (16) is more obvious for small values of SNR.

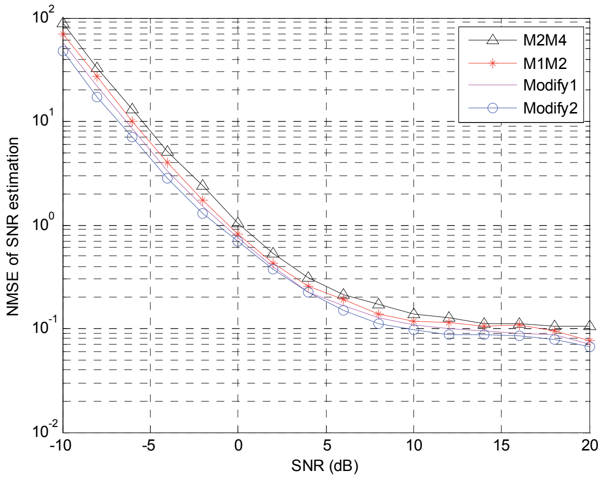

Fig. 6. NMSE of several SNR estimators vs. SNR.

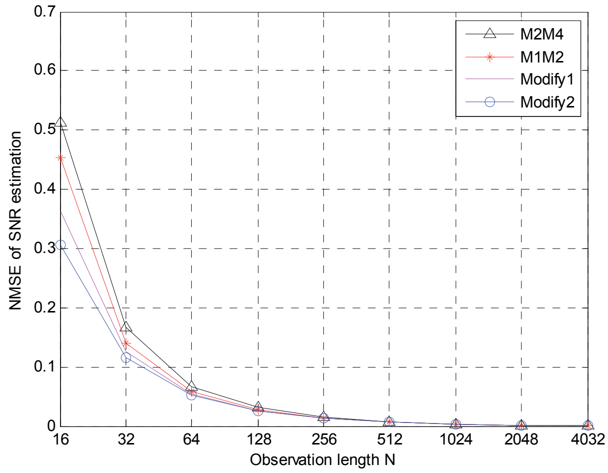

Fig. 7. NMSE of several SNR estimators vs. observation length.

In order to further examine the bias property of the estimators, the mean of the estimated SNR for each estimator is plotted versus the true SNR in Fig. 5. We find that the mean of estimation value of the Modify2 with only 32 available data can be very close to the true SNR value even when the SNR is as low as -2 dB. So the Modify2 algorithm can be used for short burst communication, such as slow frequency hop transmission.

For comparison, Fig. 6 and 7 show the normalized noise variances of the four SNR estimators versus SNR and observation length respectively. The SNR is set to be 8 dB in simulation for Fig. 7. Thanks to the modification technique, the variance of the proposed SNR estimator is lowest among all of the four estimators in both of the two figures. We can also see that the performance of M1M2 is better than the M2M4. The same conclusion is also made in [12]. Although more comparisons with other SNR estimation algorithms are not presented here, we can expect that the new estimator is superior to most of them since the M1M2 algorithm has been proved to perform best among many algorithms in [12].

6. Conclusion

A highly accurate and low bias SNR estimator is proposed for MPSK modulation in this paper. Based on the expectation of the statistics with finite observation length, a modification algorithm is derived to reduce the bias of traditional M1M2 estimator. The inverse function representing the M1M2 estimator is approximated by multi segments of cubic polynomial with high precision in the range of SNR from -10 dB to 20 dB. We also investigate the FPGA implementation method and propose practical hardware circuit for the estimator. The performances of the SNR estimator are evaluated by simulation and compared with other two estimators. It's shown that the proposed estimator performs best among all of the examined estimators. Besides, the new estimator doesn't require the knowledge of transmitted data and carrier parameters. So the SNR estimator is not sensitive to carrier parameter estimation errors. The demodulation delay can be reduced as the SNR can be estimated at the same time when carrier parameters are being estimated. What's more, it can be adopted by MPSK modulation with any order. The proposed estimator can be widely used in many fields, such as adaptive transmission, turbo decoding, power control and so on.

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