A Linear Prediction Based Estimation of Signal-to-Noise Ratio in AWGN Channel

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Most signal-to-noise ratio (SNR) estimation techniques in digital communication channels derive the SNR estimates solely from samples of the received signal after the matched filter. They are based on symbol SNR and assume perfect synchronization and intersymbol interference (ISI)-free symbols. In severe channel distortion where ISI is significant, the performance of these estimators badly deteriorates. We propose an SNR estimator which can operate on data samples collected at the front-end of a receiver or at the input to the decision device. This will relax the restrictions over channel distortions and help extend the application of SNR estimators beyond system monitoring. The proposed estimator uses the characteristics of the second order moments of the additive white Gaussian noise digital communication channel and a linear predictor based on the modified-covariance algorithm in estimating the SNR value. The performance of the proposed technique is investigated and compared with other in-service SNR estimators in digital communication channels. The simulated performance is also compared to the Cramér-Rao bound as derived at the input of the decision circuit.

Keywords: Signal-to-noise ratio estimation, in-service estimators, phase-shift keying.

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I. Introduction

A good signal-to-noise ratio (SNR) estimation technique in communication systems is needed since various receiver optimization algorithms require knowledge of the SNR for optimal performance if the SNR is time-varying [1], [2]. The performance of such communication systems can be improved if accurate SNR-estimates are available.

Many SNR estimators in digital communication channels have been proposed over the last few decades [3]. Most of these techniques derive the symbol SNR estimates solely from the received signal at the output of the matched filter (MF). The estimators assume perfect carrier and symbol synchronization while at the same time implicitly assuming intersymbol interference (ISI)-free output of the MF (the decision variable). However, in practice, multipath wireless communication gives rise to much intersymbol interference, especially in indoor and urban areas. In these ISI dominated scenarios, SNR estimators that do not presume ISI-free reception are highly desirable.

In this paper, an in-service SNR estimation technique in digital communication channels is presented. In contrast to other SNR estimators, the proposed technique can operate on data collected at the front-end of the receiver without any restriction on ISI. This will improve the SNR estimates in severe ISI channels and also help in extending the implementation of SNR estimators in systems that require SNR estimates at the input of the receiver. One such application is antenna diversity combining, where at least two antenna signal paths are communicably connected to a receiver. The combiner can use the SNR estimates obtained for each antenna signal to respectively weight each signal and thereby generate a combined output signal.

The proposed technique depends on the characteristics of the second-order moments of the additive white Gaussian noise

(AWGN) digital communication channel in estimating the SNR value. A linear predictor with coefficients obtained using the modified-covariance algorithm is used to find the power of the AWGN noise and the SNR value.

The remainder of the paper is organized as follows. Section II provides a brief introduction to the popular in-service estimators, such as squared signal-to-noise variance (SNV), second- and fourth-order moment (M_2M_4), and signal-to-variation ratio (SVR) estimators. Section III, introduces the proposed technique based on linear prediction, and section IV compares the relative performance of all the techniques. Section V concludes the paper.

To make the presentation as clear as possible, attempt has been made to adhere to a somewhat standard notational convention. Lower case boldface characters will generally refer to vectors, upper case boldface characters will generally refer to matrices, and $(.)^H$ will be used to denote the Hermitian conjugate (or complex-conjugate transpose) operation. Occasionally, conjugation is required without transposition and vice-versa, and for those operations, (.)* (conjugation) and $(.)^T$ (transposition) are used.

II. Popular In-Service SNR Estimators in AWGN Channels

In this section, we outline three SNR estimators which are widely recognized as the best among the in-service techniques that operate on one sample per symbol. The SNR of interest is the ratio of the discrete signal power to the discrete noise power at the input to the decision device at the optimal sampling instances.

A block of N_{sym} M-ary source symbols is pulse-shaped by a root raised-cosine (RRC) filter, scaled by a constant attenuation factor, and corrupted by sampled, complex AWGN. The sequence of M-ary source symbols is represented by

$$a_n = e^{j\theta_n}, \qquad \mathrm{n} \in \{0,1,2,\cdots,N_{sym}-1\}, \tag{1}$$

where θ_n is one of M phases spaced evenly around the unit circle. The pulse-shaped information signal is given by

$$m_k = \sum_n a_n h_{k-n}, \tag{2}$$

where h_k represents the RRC filter tap coefficients. The signal presented to the receiver is

$$r_k = \sqrt{s}\, m_k + \sqrt{N} z_k, \tag{3}$$

where z_k is the complex, sampled, zero-mean AWGN of unit variance, S is a signal power scale factor, and N is a noise power scale factor. The samples of the received signal after the MF can be expressed as

$$y_n = y_k \Big|_{k=nNss} = \sqrt{S} a_n g_0 + \sqrt{N} w_n, \tag{4}$$

where g_o is the peak of the full raised-cosine impulse response, and w_n represents the symbol-spaced, filtered samples.

In analyzing various in-service SNR estimators, (4) is used as the data model at the input to the decision device.

1. Squared SNV Estimator

This in-service SNR estimator is based on the first absolute moment and the second moment of the sampled output of the MF. It was introduced by Gilchriest, in 1966, for binary phase-shift keying (BPSK) signal in real AWGN [4]. The SNV estimator, as given in [4] for BPSK in real AWGN, is expressed in terms of the sampled output of the MF as

$$\hat{\rho}_{SNV} = \frac{\left[\frac{1}{N_{sym}} \sum_{n=0}^{N_{sym}-1} |y_n|\right]^2}{\frac{1}{N_{sym}-1} \sum_{n=0}^{N_{sym}-1} y_n^2 - \frac{1}{N_{sym}(N_{sym}-1)} \left[\sum_{n=0}^{N_{sym}} |y_n|\right]^2}. \tag{5}$$

2. Second- and Fourth-Order Moments (M_2M_4) Estimator

An early mention of the application of second- and fourth-order moments to the separate estimation of carrier strength and noise strength in real AWGN channels was made in 1967 by Benedict and Soong [5]. In 1994, Matzner and Engleberger [6] gave a detailed derivation of the estimator for real signals. In 2000, Pauluzzi and Beaulieu extended the derivation of the M_2M_4 to complex AWGN channels [3].

The derivation provided in [3] for complex channels may be sketched as follows.

Let M_2 denote the second moment of y_n as

$$\begin{aligned} M_2 &= E\{y_n y_n^*\} \\ &= S\, E\{|a_n|^2\} + \sqrt{SN} E\{a_n w_n^*\} + \sqrt{SN} E\{a_n^* w_n\} + NE\{|w_n|^2\}, \end{aligned} \tag{6}$$

and let M_4 denote the fourth moment of y_n as

$$\begin{aligned} M_4 &= \mathbf{E}\{(y_n y_n^*)^2\} \\ &= S^2 \mathbf{E}\{|a_n|^4\} + 2S\sqrt{SN} \cdot \left(\mathbf{E}\{|a_n|^2 a_n w_n^*\} + \mathbf{E}\{|a_n|^2 a_n^* w_n\}\right) \\ &+ SN\left(\mathbf{E}\{(a_n w_n^*)^2\} + 4\mathbf{E}\{|a_n|^2 |w_n|^2\} + \mathbf{E}\{(a_n^* w_n)^2\}\right) \\ &+ 2N\sqrt{SN}\left(\mathbf{E}\{|w_n|^2 a_n w_n^*\} + \mathbf{E}|w_n|^2 a_n^* w_n\right) + N^2 \mathbf{E}\{|w_n|^4\}, \end{aligned} \tag{7}$$

where $\mathbf{E}\{.\}$ is the expected value. Assuming that the signal and noise are zero-mean independent random processes and the in-phase and quadrature components of the noise are independent, (6) and (7) reduce to

$$M_2 = S + N \tag{8}$$

and

$$M_4 = k_a S^2 + 4SN + k_w N^2, \tag{9}$$

where $k_a = \mathbf{E}\left\{|a_n|^4\right\} / \mathbf{E}\left\{|a_n|^2\right\}^2$ and $k_w = \mathbf{E}\left\{|w_n|^4\right\} / \mathbf{E}\left\{|w_n|^2\right\}^2$. Solving for S and N, we obtain

$$\hat{S} = \frac{M_2\left(k_w - 2\right) \pm \sqrt{\left(4 - k_a k_w\right) M_2^2 + M_4\left(k_a + k_w - 4\right)}}{k_a + k_w - 4} \tag{10}$$

and

$$\hat{N} = M_2 - \hat{S}. \tag{11}$$

The estimator formed as the ratio of $\hat{S}$ to $\hat{N}$ is denoted as the M_2M_4 estimator. For any M-ary PSK signal, k_a =1 and for complex noise, $k_w = 2$, so that

$$\hat{\rho}_{M_2M_4} = \frac{\sqrt{2M_2^2 - M_4}}{M_2 - \sqrt{2M_2^2 - M_4}}. \tag{12}$$

3. SVR Estimator

The SVR estimator, described by Brandão and others in [7], is a moment-based method developed to monitor channel quality in multipath fading channels, which can also be applied as a measure of channel quality in an AWGN channel.

The SVR estimator is a function of the parameter

$$\beta = \frac{\mathbf{E}\left\{y_n y_n^* y_{n-1} y_{n-1}^*\right\}}{\mathbf{E}\left\{\left(y_n y_m^*\right)^2\right\} - \mathbf{E}\left\{y_n y_n^* y_{n-1} y_{n-1}^*\right\}}. \tag{13}$$

The term $\mathbf{E}\left\{\left(y_n y_m^*\right)^2\right\}$ is M_4 of the M_2M_4 method. The other term in (13) simplifies to

$$\mathbf{E}\left\{y_n y_n^* y_{n-1} y_{n-1}^*\right\} = S^2 + 2SN + N^2. \tag{14}$$

Writing S/N as ρ and substituting (9) and (14) into (13), the result is

$$\beta = \frac{\rho^2 + 2\rho + 1}{\left(k_a - 1\right)\rho^2 + 2\rho + \left(k_w - 1\right)}, \tag{15}$$

which may be solved for ρ to yield the general SVR estimator for the complex channel as

$$\hat{\rho}_{SVR,complex} = \beta - 1 + \sqrt{\beta\left(\beta - 1\right)}, \tag{16}$$

where for M-ary PSK signal, k_a =1 and for complex noise, $k_w = 2$.

For real signals,

$$\beta = \frac{\mathbf{E}\left\{y_n^2 y_{n-1}^2\right\}}{\mathbf{E}\left(y_n^4\right) - \mathbf{E}\left\{y_n^2 y_{n-1}^2\right\}}, \tag{17}$$

where $\mathbf{E}\left\{y_n^4\right\}$ is given by

$$M_4 = k_a S^2 + 6SN + k_w N^2, \tag{18}$$

and $\mathbf{E}\left\{y_n^2 y_{n-1}^2\right\}$ simplifies to the same expression as (14). Substituting (18) and (14) into (17), and assuming k_a = 1 and $k_w = 3$ for BPSK-modulated signal in real AWGN, S/N is given by

$$\hat{\rho}_{SVR,real} = \left(2\beta - 1\right) + \sqrt{2\beta\left(2\beta - 1\right)}. \tag{19}$$

The previously discussed in-service SNR estimators will be used as benchmarks for comparison with the proposed technique.

III. The Linear Prediction (LP)-Based Estimator

In AWGN digital communication channels, consider the received signal at the front end of receiver as

$$x(n) = s(n) + w(n), \tag{20}$$

where $x(n)$ denotes the signal and $w(n)$ the noise. Often, this additive noise is assumed to be zero mean AWGN and uncorrelated with the signal. In this case, the autocorrelation of the measured data, $x(n)$, is given as

$$r_x(k,l) = r_s(k,l) + r_w(k,l)\ . \tag{21}$$

Assuming $x(n)$, a wide-sense stationary random process, the autocorrelation $r_x(k,l)$ depends only on the difference, $m = k - l$. Thus, (21) may be rewritten as

$$r_x(m) = r_s(m) + r_w(m). \tag{22}$$

Because a zero-mean AGWN $w(n)$ models the nondeterministic part of (20), this process is uncorrelated with itself for all lags, except at m = 0, and its autocorrelation sequence (ACS) has the following form:

$$r_w(m) = \sigma^2 \delta(m), \tag{23}$$

where σ^2 is the variance of noise, and $\delta(m)$ is the discrete delta sequence.

Since the autocorrelation sequence of $s(n)$ is a conjugate symmetric function of m, $r_s(m) = r_s^*(-m)$ with the amplitude upper bounded by its value at $m = 0$. The noise part of (20), which tends to affect each sample in the time domain, confines its effect to the zero-offset sample in the second order statistics domain, making it possible to reduce the problem of noise variance estimation in AWGN systems to $r_s(0)$ estimation.

Assume that we have (N+1)-point ACS $r_x(-N)$, $r_x(-N+1)$,⋯, $r_x(0)$,estimated from the received signal at the front end of digital receiver. Between the N+1 autocorrelation samples, the zero lag noise-free autocorrelation sample $r_s(0)$ is missing. The objective is to estimate $r_s(0)$ using the remaining N samples, thereby obtaining the power of additive noise which leads to the SNR value.

Different techniques can be used to predict the value of $r_s(0)$ from the remaining N autocorrelation samples. Among the different prediction techniques, the modified-covariance technique remains among the best. Since the modified-covariance method is well documented [8]-[10] a brief description is given here.

Step 1. From the available autocorrelation sequence, the matrix of the forward linear prediction errors e^f is given as

$$\begin{bmatrix} e_p^f(-1) \\ e_p^f(-2) \\ \vdots \\ e_p^f(-N+p+1) \\ e_p^f(p+1) \\ e_p^f(p+2) \\ \vdots \\ e_p^f(N) \end{bmatrix} = \begin{bmatrix} r_x(-1) \\ r_x(-2) \\ \vdots \\ r_x(-N+p+1) \\ r_x(p+1) \\ r_x(p+2) \\ \vdots \\ r_x(N) \end{bmatrix} - \begin{bmatrix} r_x(-2) & r_x(-3) & \cdots & r_x(-1-p) \\ r_x(-3) & r_x(-4) & \cdots & r_x(-2-p) \\ \vdots & \vdots & \ddots & \vdots \\ r_x(-N+p) & r_x(-N+p-1) & \cdots & r_x(-N) \\ r_x(p) & r_x(p-1) & \cdots & r_x(1) \\ r_x(p+1) & r_x(p) & \cdots & r_x(2) \\ \vdots & \vdots & \ddots & \vdots \\ r_x(N-1) & r_x(N-2) & \cdots & r_x(N-p) \end{bmatrix} \begin{bmatrix} a_p^f(1) \\ a_p^f(2) \\ a_p^f(3) \\ \vdots \\ a_p^f(p) \end{bmatrix}, \tag{24}$$

where the $a_p^f(k)$ are the forward linear prediction coefficients, and p is the order of forward predictor. Equation (24) can be written in a compact form as

$$\boldsymbol{e}^f = \boldsymbol{r}^f - \boldsymbol{R}^{\mathrm{f}}\, \boldsymbol{a}_{\mathrm{p}}^{\mathrm{f}}. \tag{25}$$

Step 2. In similar way to step 1, and in order to double the prediction errors, form the matrix of the backward linear prediction errors $\mathbf{e}^{\mathrm{b}}$, given as

$$\begin{bmatrix} e_m^b(-N) \\ e_m^b(-N+1) \\ \vdots \\ e_m^b(-m-1) \\ e_m^b(1) \\ e_m^b(2) \\ \vdots \\ e_m^b(N-m-1) \end{bmatrix} = \begin{bmatrix} r_x(-N) \\ r_x(-N+1) \\ \vdots \\ r_x(-m-1) \\ r_x(1) \\ r_x(2) \\ \vdots \\ r_x(N-m-1) \end{bmatrix} - \begin{bmatrix} r_x(-N+1) & r_x(-N+2) & \cdots & r_x(-N+m) \\ r_x(-N+2) & r_x(-N+3) & \cdots & r_x(-N+m+1) \\ \vdots & \vdots & \ddots & \vdots \\ r_x(-m) & r_x(-m+1) & \cdots & r_x(-1) \\ r_x(2) & r_x(3) & \cdots & r_x(m+2) \\ r_x(3) & r_x(4) & \cdots & r_x(m+3) \\ \vdots & \vdots & \ddots & \vdots \\ r_x(N-m) & r_x(N-m+1) & \cdots & r_x(N) \end{bmatrix} \begin{bmatrix} a_m^b(1) \\ a_m^b(2) \\ a_m^b(3) \\ \vdots \\ a_m^b(m) \end{bmatrix}, \tag{26}$$

where the $a_p^b(k)$ are the backward linear prediction coefficients, and p is the order of the backward predictor. Equation (26) can be written in compact form as

$$\boldsymbol{e}^b = \boldsymbol{r}^b - \boldsymbol{R}^{\mathrm{b}}\, \boldsymbol{a}_{\mathrm{p}}^{\mathrm{b}}. \tag{27}$$

Since $a_p^f(k) = \left(a_p^{*b}(k)\right)$, (27) can be rewritten in terms of the forward prediction coefficient as

$$\boldsymbol{e}^{*b} = \boldsymbol{r}^{*b} - \boldsymbol{R}^{*b} \boldsymbol{a}_p^f. \tag{28}$$

Step 3. Because both directions have similar statistical information, it seems reasonable to combine the linear prediction error statistics of both forward and backward errors in order to generate more error points [8]. The net result should be an improved estimate of the predictor coefficients. The $2\times(N\text{-}p)$ forward and the $2\times(N\text{-}p)$ backward linear prediction errors may be summarized concisely by the matrix-vector product:

$$\boldsymbol{e} = \begin{bmatrix} \boldsymbol{e}^f \\ \boldsymbol{e}^{*b} \end{bmatrix} = \begin{bmatrix} \boldsymbol{r}^f \\ \boldsymbol{r}^{*b} \end{bmatrix} - \begin{bmatrix} \boldsymbol{R}^f \\ \boldsymbol{R}^{*b} \end{bmatrix} \begin{bmatrix} a_p^f(1) \\ \vdots \\ a_p^f(p) \end{bmatrix},$$

$$\boldsymbol{e} = \boldsymbol{r} - \boldsymbol{R}\boldsymbol{a}_p^f \tag{29}$$

Step 4. Obtain the predictor coefficients by solving (29) for the least squared error as follows. The average of the forward and backward linear prediction squared errors over the available data, is given by

$$\rho_p = \sum_n \left|e_p^f(n)\right|^2 + \sum_n \left|e_p^b(n)\right|^2 = \boldsymbol{e}^T \boldsymbol{e}\,. \tag{30}$$

By substituting (29) into (30), we may explicitly express the dependence of the sum of squared errors on the predictor coefficients as

$$\rho_p = \boldsymbol{r}^T \boldsymbol{r} - \boldsymbol{r}^T \boldsymbol{R}\ \boldsymbol{a}_p^f - \boldsymbol{a}_p^{f\,T} \boldsymbol{R}^T \boldsymbol{r} + \boldsymbol{a}_p^{f\,T} \boldsymbol{R}^T \boldsymbol{R}\boldsymbol{a}_\mathrm{p}^{fT}. \quad (31)$$

Then, by differentiating (31) with respect to $\boldsymbol{a}_p^f$, we get the following gradient vector, given by

$$\begin{aligned}\frac{\partial \rho}{\partial \boldsymbol{a}_p^f} &= -2\boldsymbol{R}^T \boldsymbol{r} + 2\boldsymbol{R}^\mathrm{T} \boldsymbol{R}\ \boldsymbol{a}_\mathrm{p}^\mathrm{f} \\ &= -2\boldsymbol{R}^\mathrm{T} \boldsymbol{e}\ .\end{aligned} \quad (32)$$

As it is clear that the sum of squared errors reaches its minimum value when the gradient vector is zero, from (32) we may deduce that

$$\boldsymbol{R}^T \boldsymbol{R}\ \boldsymbol{a}_\mathrm{p}^\mathrm{f} = \boldsymbol{R}^T \boldsymbol{e}\ . \quad (33)$$

Thus, the predictor coefficients which give the least squared errors are obtained as a solution to (33). However, this solution is unique only when the nullity of the matrix $\boldsymbol{R}$ is zero [11]. In other words, the least-squares solution is unique, when the matrix $\boldsymbol{R}$ is of full rank. When this condition is satisfied, the matrix $\boldsymbol{R}^T\boldsymbol{R}$ is nonsingular and the solution is unique, given as

$$\begin{aligned}\boldsymbol{a}_p^f &= \left(\boldsymbol{R}^\mathrm{T} \boldsymbol{R}\right)^{-1} \boldsymbol{R}^\mathrm{T} \boldsymbol{e} \\ &= \boldsymbol{R}^{\#} \boldsymbol{e}\ ,\end{aligned} \quad (34)$$

where $\boldsymbol{R}^{\#}$ is called the pseudoinverse of the matrix $\boldsymbol{R}$, given as

$$\boldsymbol{R}^{\#} = \left(\boldsymbol{R}^\mathrm{T}\boldsymbol{R}\right)^{-1} \boldsymbol{R}^\mathrm{T}. \quad (35)$$

Step 5. Use predictor coefficients and the prior p autocorrelation samples to zero-offset the autocorrelation value in order to predict the power of noiseless signal $s(t)$ of (20):

$$r_s(0) = \sum_{k=1}^{p} a_p^f(k) r_x(-k). \quad (36)$$

Step 6. Find the power of AWGN as $\sigma^2 = r_x(0) - r_s(0)$ and SNR estimation as $\dfrac{r_s(0)}{\sigma^2}$.

IV. Performance Comparisons

The best SNR estimator is unbiased (or exhibits the smallest bias) and has the smallest variance. The statistical mean squared error (MSE) reflects both the bias and the variance of an SNR estimate and is given by

$$MSE\left\{\hat{\rho}\right\} = E\left\{\left(\hat{\rho} - \rho\right)^2\right\}, \quad (37)$$

where $\hat{\rho}$ is an estimate of the SNR, and ρ is the true SNR.

1. Cramer-Rao Bound

In order to assess the absolute performance of each estimator, the CRB is used as a reference. Thomas [12] derived Cramer-Rao Bound the (CRB) for real channels, and based on [12] and [13], Pauluzzi and Beaulieu extended the derivation to complex channels [3]. The normalized CRB by ρ^2 for an unbiased SNR estimator in complex AWGN channel expressed in terms of the normalized MSE (NMSE) is given by

$$NMSE\left\{\hat{\rho}\right\} = \frac{MSE\left\{\hat{\rho}\right\}}{\rho^2} = \frac{var\left\{\hat{\rho}\right\}}{\rho^2} \geq \frac{2}{\rho N_{sym}} + \frac{1}{N_{ss} N_{sym}}, \quad (38)$$

where N_{sym} is the number of symbols, and N_{ss} is the number of samples per symbol. The CRB for unbiased SNR estimators in real channels may be expressed in terms of the normalized MSE as

$$NMSE\left\{\hat{\rho}\right\} \geq 2\left(\frac{2}{\rho N_{sym}} + \frac{1}{N_{ss} N_{sym}}\right). \quad (39)$$

It is necessary to emphasize here that the above formulas for CRB are derived for estimators operating on data collected at the input to the decision device.

2. Results and Discussion

Figures 1 and 2 compare the performance of the LP, SNV, M_2M_4, and SVR estimators for BPSK-modulated signal in a real AWGN channel. The performance of each estimator is calculated in terms of MSE normalized to true SNR value.

Figure 1 shows the performance of the considered estimators with 64 symbols, collected at the input to the decision device for SNV, M_2M_4, and SVR and at the front-end of receiver for the LP estimator. Figure 2 shows the performance of the same SNR estimators but with $N_{sym} = 512$ symbols.

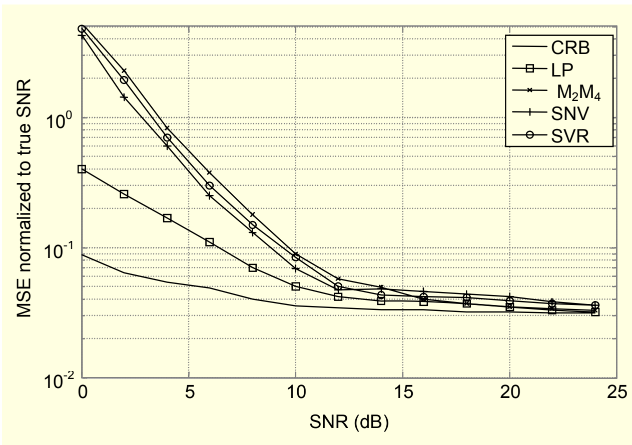

Fig. 1. Normalized MSE with BPSK signals in real AWGN ($N_{sym} = 64$).

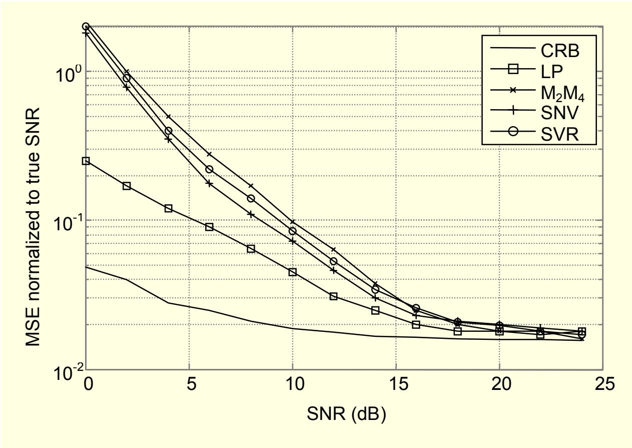

Fig. 2. Normalized MSE with BPSK signals in real AWGN (N_{sym} = 512).

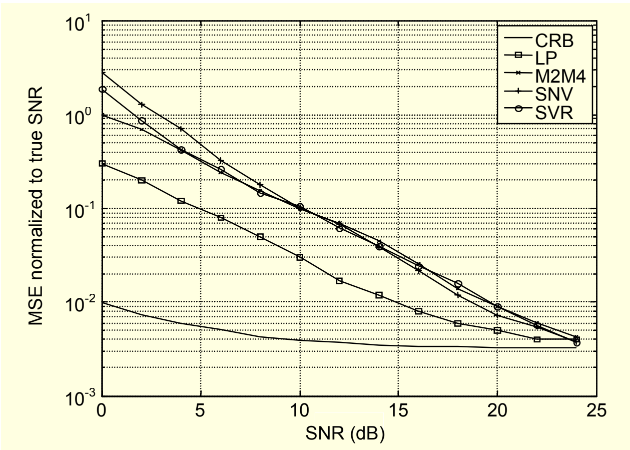

Fig. 3. Normalized MSE with 8-ary signals in complex AWGN (N_{sym} = 64).

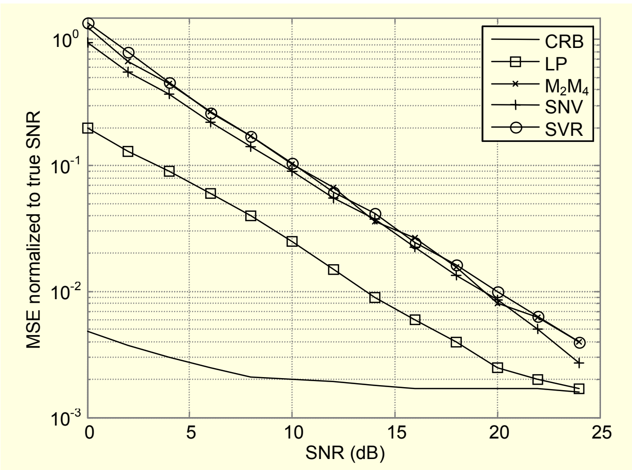

Fig. 4. Normalized MSE with 8-ary signals in complex AWGN (N_{sym} = 512).

From Figs. 1 and 2, it is immediately apparent that for real digital communication channels, the NMSE curves of the LP estimator are significantly lower than those of other estimators. This better performance by the LP estimator is especially clear at SNR < 10 dB for N_{sym} = 64 and at SNR < 12 dB for N_{sym} = 512.

Figures 3 and 4 compare the performance of the LP, SNV, M_2M_4, and SVR estimators for 8-ary signal in complex AWGN channel with N_{sym} = 64 and N_{sym} = 512, respectively. Figure 3 clearly shows that with a relatively small block of symbols, N_{sym} = 64, the LP outperforms other estimators up to nearly SNR = 15 dB and approaches their NMSE values as well as their CRB for higher values. In Fig. 4, where the simulation is run with a relatively large block of symbols, the LP shows a constant difference in performance from other in-service estimators over the entire considered range of SNR values.

V. Conclusion

In contrast to other in-service SNR estimators that derive the SNR estimates solely from samples at the input to the decision device, a novel estimator was presented that can operate at the front-end and at the input to the decision device of the receiver. The performance of the proposed technique was tested and compared with other in-service estimators at different block lengths and with different types of modulation. The range of interest for the SNR extended between 0 dB and 25 dB. In the simulation, two types of modulation were used with block lengths of 64 and 512 symbols. The BPSK was used for the real communication channel and an 8-ary PSK was used for the complex channel. The results demonstrate that the proposed estimator achieves better performance in comparison to other estimators and prove its efficiency and reliability in estimating SNR. Since complexity is also a factor to consider, the developed estimator is relatively easy to implement.

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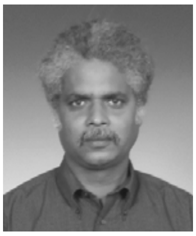

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