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Research Article

Enhancement of Noise Performance in Digital Receivers by Over Sampling the Received Signal

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Abstract

In wireless channel the noise has a zero mean. This channel property can be used in the enhancement of the noise performance in the digital receivers by oversampling the received signal and calculating the decision variable based on the time average of more than one sample of the received signal. The averaging process will reduce the effect of the noise in the decision variable that will approach to the desired signal value. The averaging process works like a filter that reduces the noise power at its output according to its averaging interval. Although the power spectrum of the noise does not change according to the averaging process, the noise variance at the decision variable will be smaller than the channel noise variance. This paper studies this idea and show how the performance of digital receivers can be enhanced by oversampling the received signal. This paper shows another treatment method to the noise problem in digital modulation systems.

Keywords : Wireless channel; Noise performance; Signal; Averaging interval.

1 Introduction

Noise is the main corrupting element in any communication system. It is unavoidable interference source in all communication channels and the main source of errors and performance degradations. A lot of researches have been done to minimize the effect of the noise or to try to cancel it. Some of these researches depend on minimizing the mean square error value between the channel noise and another noise like signal which generated from a noisy source and an adaptive filter [1, 2, 6].Other approaches use the recursive least square (RLS) algorithm to minimize the error square between the estimated signal with reduced noise and the noisy measured signal [3]. The noise reduction receivers based on RLS algorithm are faster than those based on LMS algorithm however the LMS algorithm can reduce the noise power more than the RLS algorithm. Another research shows that the noise and signal feature detection problem can be converted to statistical hypotheses tests based on the sample correlation in different orientations [4].This algorithm provide ways of measuring the degree of noise with respect to the degree of signal feature, and its adaptive noise reduction filtering framework provides good performance with respect to the adaptive algorithms when the underlying noises are from Gaussian or non-Gaussian distributions. In addition to adaptive algorithms, channel coding may be used to enhance the noise reduction process as shown in [5]. The previous trials are depending on a complex signal processing unit that complicates the receiver structure however the performance enhancement is not great especially with the white noise case. On the other

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hand, we did not find any research based on the fact that the noise in wireless channel has a zero mean. This is an important statistical property of the noise that may be used to trim down the effect of the noise on the transmitted data. Our work in this paper is based on the wireless channel noise characteristics and the estimation theory that are shown in [8, 9, 10]. It is arranged as follows. Section 2 shows the effect of the oversampling process of the received signal on the noise mean of the decision variable. Section 3 applies the proposed idea on the BPSK system which is an example of a wireless system however Section 4 shows the oversampling gain effect on the BPSK probability of error formula. Simulation results are shown in section 5. Finally the conclusions are represented in Section 6.

2 The effect of oversampling on the noise signal and the decision variable

In wireless communication channel, the noise signal that corrupts the desired transmitted signal is a sample function of a zero mean random process with a certain variance . The noise mean can be estimated by calculating the time average of the discrete samples of the noise sample function n(t) which will approach to the statistical average of the noise process when the averaging period is large as shown in the following equation.

$$\lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} n_i = E[n(t)] \tag{2.1}$$

The last statement is true if the noise process is Ergodic which is the case for all physical wireless communication channels [8],therefore the time average will be used instead of the statistical average to estimate the noise mean and variance as shown in sections (*2.1*) and (*2.2*). The noise in all communication channels is additive. Thus, the decision variable in any detector consists mainly from two components. One is due to the desired signal and the other is the noise signal component.

$$d = s + n \tag{2.2}$$

d d is the decision variable or the sufficient statistic, s is the desired signal component which has a constant value during the symbol interval, and n is the noise signal component which is a random variable. The statistical mean and variance of the decision variable are represented by equations (**??**) and (**??**) respectively.

$$E[d] = E[s+n] = E[s] + E[n] = s \tag{2.3}$$

$$var[d] = var[s+n] = var[n] \tag{2.4}$$

If the decision variable in the last equations is formed based on a single sample of the desired signal and the noise functions, the variance of the decision variable will be the same as the variance of the channel noise function . But if the decision variable is formed based on the average of more than one observation sample, the variance of the decision variable will be decreased by a factor proportional to the number of samples in the average process. Sections (*2.1*) and (*2.2*) give the mathematical proof of this observed result for the white and color noise cases respectively.

2.1 White noise case

In white noise case, the noise samples are independent. The estimation theory said that if N statistically independent samples are taken from a sample function of the noise process to estimate the noise mean, the estimated mean will be

$$\hat{\mu}_n = \frac{1}{N}\sum_{i=1}^{N} n_i \tag{2.5}$$

ni is the ith sample of the white noise function n(t) during one bit interval. This average is also a random variable. Its mean is equal to the actual noise mean and its variance is depending on the used number of samples.

$$E[d] = E[\hat{\mu}_n] = \frac{1}{N}\sum_{i=1}^{N} E[n_i] = 0 \tag{2.6}$$

$$\begin{aligned} var[d] = var[\hat{\mu}_n] &= var[\frac{1}{N}\sum_{i=1}^{N} n_i] \\ &= \frac{1}{N}\sum_{i=1}^{N} var[n_i] = \frac{\sigma_n^2}{N} \end{aligned} \tag{2.7}$$

The last two equations (2.6), (2.7) of the mean and variance of the estimated noise averages how that if the number of noise samples is increased, the estimated noise mean will approach to zero with a variance that is inversely proportion to the number of samples used in the estimation process. This observation will be used in Section (3) to enhance the performance of BPSK system which is an example of a wireless communication system.

2.2 Color noise case

The previous idea of reducing the variance of the decision variable by averaging it over N samples needs the zero mean noise samples to be uncorrelated (white). This case is achieved in all communication channels where the channel noise is white and Gaussian. But for the case of colored noise samples, equations (2.6), (2.7) don't hold because the noise samples are correlated. The correlated noise samples are produced when the white noise samples pass through a system filter. The variance of the produced samples will be reduced according to the system filter normalized bandwidth Bn.

$$\sigma_{nc}^2 = \frac{\sigma_n^2 B}{F_s} = \sigma_n^2 B_n \tag{2.8}$$

Fs is the sampling frequency and B is the bandwidth of the system filter. From equation (2.8), the color noise variance will be smaller than the white noise variance. The variance of the estimated mean in the case of correlated noise samples is

$$var(\hat{\mu}_{nc}) = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N} E[(n_{ci}-\mu_{nci})(n_{cj}-\mu_{ncj})] \tag{2.9}$$

After some mathematical manipulations, the variance will be

$$var(\hat{\mu}_{nc}) = \frac{\sigma_{nc}^2}{N} + \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j\neq i}^{N} \rho_{ij}\sigma_{nc}^2$$
$$\because \rho_{ij} = E[n_i n_j] = \rho_{i-j}$$
$$\because var(\hat{\mu}_{nc}) = \frac{\sigma_{nc}^2}{N} + \frac{\sigma_{nc}^2}{N}\sum_{i=1}^{N-1}\rho_i \tag{2.10}$$

ρ_j is the correlation coefficient between two noise samples vectors with j sample shift between them. From equation (2.10), it is clear that the averaging process of the color noise samples reduces the variance of the color noise by a factor depends on the number of samples in the averaging process and the correlation coefficient between the noise samples. The variance of the estimated average of color noise samples has an upper bound equals to the color noise variance and a lower bound equals to the white noise variance divided by N.

$$\frac{\sigma_n^2}{N} < var(\hat{\mu}_n) < \sigma_{nc}^2 \tag{2.11}$$

As long as the variance of the correlated noise samples depends on the sampling frequency, so oversampling the uncorrelated noise samples will reduce the variance of the correlated noise samples produced at the output of the system filter. A whitening filter may be used to convert the noise samples to uncorrelated noise samples. But this will complicate the receiver structure and its enhancement on the performance - due to the conversion of the color noise to white noise - can be achieved by the oversampling process. Simulation results agree with the proposed idea. The correlated noise samples variance will be decreased by a factor greater than N and depend on the noise bandwidth.

3 Theoretical analysis of the proposed idea on BPSK system

BPSK is a classical digital modulation system that uses two different phase angles to transmit binary data. Equation (3.12) shows the discrete form of the transmitter BPSK signal $\boldsymbol{s}_k$ for the $\boldsymbol{k}^{th}$ symbol.

$$s_k(N) = b_k\sqrt{2}cos(2\pi f_n n),$$
$$KN < n \leq (k+1)N,\ 0 < k < K \tag{3.12}$$

$\boldsymbol{K}$ is the number of transmitted binary symbols, $\boldsymbol{b}_k$ is the $\boldsymbol{k}^{th}$ binary symbol, $\boldsymbol{b}_k$ takes a value of 1 or -1 according to the binary transmitted symbols 1 or 0 respectively. $\boldsymbol{f}_n$ is the normalized frequency which equals to the ratio between the carrier frequency and the sampling frequency. Integral number of carrier cycles is assumed through the bit interval. N is the number of samples per bit

$$N = \frac{T_b}{T_s} \tag{3.13}$$

The used discrete orthonormal basic function ψ_n is a sinusoidal function.

$$\psi_n = \sqrt{2}cos(2\pi f_n n) \tag{3.14}$$

The transmitted symbol $\boldsymbol{s}_k$ The transmitted symbol $\boldsymbol{E}_t$. Assuming that the transmitted symbols pass through a linear white Gaussian channel, the received discrete signal will be

$$r(n) = s_k(n) + w(n) \tag{3.15}$$

$\boldsymbol{w(n)}$ is a discrete sample function of a white Gaussian noise process $\mathbf{c}(\boldsymbol{t})$ with a zero mean and σ_w^2 variance. The receiver correlates the received signal with the complex conjugate of the used orthonormal basic function $\psi(n)$ to form the decision variable $\boldsymbol{y}_k$. Equation (3.16) represents the output of the discrete correlator in the receiver.

$$y_k = \sum_{n=1}^{N} b_k 2cos(2\pi f_n n)cos(2\pi f_n n) + \sum_{n=1}^{N} W(n)\sqrt{2}cos(2\pi f_n n) \tag{3.16}$$

In vector notation, the discrete correlator output is:

$$\begin{aligned} y_k &= s_k^T \varphi + w^T \varphi = b_k \varphi^T \varphi + w^T \varphi \\ &= b_k + z_k \end{aligned} \tag{3.17}$$

$\boldsymbol{b}_k$ has a constant value during the symbol time interval $\boldsymbol{T}_b$ but $\boldsymbol{z}_k$ is a Gaussian random variable, so $\boldsymbol{y}_k$ is a Gaussian random variable. Deep looking in equation (3.17) shows that $\boldsymbol{y}_k$ is the scaled estimated average of the received samples during the symbol interval $\boldsymbol{T}_b$ and $\boldsymbol{z}_k$ is the scaled estimated average of the noise samples during the same interval. $\boldsymbol{z}_k$ represents also the time average of the noise samples during the normalized symbol interval N. This time average or the estimated average of the noise samples is a random variable in natural and its mean and its variance are related to the mean and variance of the noise samples that have been used in the calculation of this time average. Equations (3.18) and (3.19) show the statistics of the time average of the scaled noise samples.

$$E[z_k] = E\left[\frac{1}{N}\sum_{n=1}^{N} w(n)\sqrt{2}cos(2\pi f_n n)\right] = \frac{1}{N}\sum_{n=1}^{N} E[w(n)]\sqrt{2}cos(2\pi f_n n) = 0 \tag{3.18}$$

$$var[z_k] = var\left[\sum_{n=1}^{N} w(n)\sqrt{2}cos(2\pi f_n n)\right] = \frac{1}{N^2}\sum_{n=1}^{N} E[w^2(n)]2cos^2(2\pi f_n n) = \frac{\sigma_w^2}{N} \tag{3.19}$$

The expected value of $\boldsymbol{y}_k$ equals to $\boldsymbol{b}_k$because the expected value of $\boldsymbol{z}_k$ equals zero.The variance of the decision variable $\boldsymbol{y}_k$ equals to the variance of the time average $\boldsymbol{z}_k$.

$$E[y_k] = E[b_k + z_k] = b_k + E[z_k] = b_k \tag{3.20}$$

$$var(y_k) = var(b_k + z_k) = var(z_k) = \frac{\sigma_w^2}{N} \tag{3.21}$$

This result in the discrete domain differs from that in the continuous domain where the variance of the decision variable in the continuous domain equals to the variance of the channel noise [9]. The continuous domain case is a special case of the discrete domain result if the number of samples per symbol is one, or a single value of noise sample is assumed to be constant in all the interval of the symbol. But this is not true because the noise varies during the symbol interval. In continuous signal detection, the decision variable y_k is formed by the integration of the received signal $r_k(t)$ multiplied by the orthonormal basic function $\psi(t)$.

$$y_k = \frac{1}{T_b}\int_0^{T_b} r_k(t)\psi^*(t)dt \tag{3.22}$$

The integration is done over the bit period, so the decision variable takes the average of the desired and the noise signals over that period. If more than one sample of the received signal is used in the average calculation, the signal to noise ratio at the output of the correlator will be smaller than the signal to noise ratio at the input of the correlator. To use more than one sample of the received signal, it should be oversampled by a sample frequency equals to

$$F_s = NR_b \tag{3.23}$$

$\boldsymbol{N}$ is the number of samples per bit and $\boldsymbol{R}_b$ is the data bit rate. By over sampling the received signal and taking the average of these samples, the decision variable will get closer to the desired signal value and the noise samples average will get closer to the statistical noise mean which is zero.

Figure (1) shows the power spectrum density of the base band channel noise signal and the power spectrum density of the average noise samples that affects on the decision variable. The channel noise samples have a constant power at the input of the correlator detector.

In Figure (1(a)), the channel noise bandwidth equals $\boldsymbol{f_s}$. For the case of single sample detection, the sampling frequency equals to the bit rate $\boldsymbol{R_b}$. The channel noise power is equal to the decision variable noise power.

$$P_{dn} = P_{cn} = \int_{-R_b/2}^{R_b/2} N_{cn}(f)df \\ = N_o R_b, \quad f_s = R_b \qquad (3.24)$$

$\mathbf{N}_o$ Nois the channel noise power spectrum density value. On the other hand, if $\boldsymbol{N}$ samples are used in the detection process, the sampling frequency will equal to $\boldsymbol{NR_b}$ as shown in equation (3.23). Although the channel noise power is constant, the noise power spectrum density will be decreased when the noise bandwidth is increased due to the averaging process of $\boldsymbol{N}$ noise samples in the correlator to form the decision variable, therefore the decision variable noise power in the signal bandwidth $\boldsymbol{R_b}$ will be smaller than the channel noise power.

$$P_{dn} = \int_{-R_b/2}^{R_b/2} N_{cn}(f)df = N_o R_b \qquad (3.25)$$

$$N_o^{'} = \frac{N_o}{N} \qquad (3.26)$$

The performance of binary signaling systems in white noise channel is controlled by the signal to noise ratio of the decision variable. This ratio differs from the channel signal to noise ratio at the input of the detector. The channel signal to noise ratio is defined as

$$SNR_C = \frac{\text{Signal power}}{\text{Channel noise power}} = \frac{P_s}{P_{cn}} \qquad (3.27)$$

The signal power is related to the bit energy as

$$P_s = E_b R_b, \quad E_b = \int_0^{T_b} |p(t)|^2 dt \qquad (3.28)$$

$\boldsymbol{p(t)}$ is the bit pulse shape. The channel signal to noise ratio is related to the decision variable signal to noise ratio by the following equation.

$$SNR_c = \frac{E_b R_b}{N_o R_b / N} = N \frac{E_b}{N_o} = N\, SNR_c \qquad (3.29)$$

In all classical communication literatures, the channel signal to noise ratio is used as the decision variable signal to noise ratio assuming that the receiver front end before the detector is noise free. This is true if the detector forms the decision variable by observing only one sample during the bit interval. But this is not the case of the correlator detector which forms the decision variable by integrating the multiplication between the received signal with a suitable basics orthonormal function over the symbol interval.

4 Adding the oversampling gain effect on the expression of the BPSK system probability of error

We areready nowto add a correction factor in the equation of the probability of error in BPSK system when the channel SNR is used. This correction factor represents the oversampling gain that is achieved by oversampling the received signal and averaging the noise samples during the symbol period. The classical probability of error equation of BPSK system is:

$$P_e = \frac{1}{2} erfc\left(\sqrt{\frac{E_b}{N_o}}\right) \qquad (4.30)$$

This equation relates the system probability of error with the channel SNR where $\boldsymbol{N_o}$ is the power spectrum density of the channel noise and $\boldsymbol{E_b}$ is the transmitted signal energy per bit. However according to the previous discussion this is only true if single sample of the received signal is used in the calculation of the decision variable. On the other hand, if N samples of the received signal are used, the decision variable SNR will be increased by a factor of N. This factor is the oversampling gain which represents the number of the samples of the received signal per symbol period. Consequently, the proposed probability of error for BPSK will depend on the decision variable SNR instead of the channel SNR as shown in the following equation:

$$P_e = \frac{1}{2} erfc\left(\sqrt{\frac{E_b}{N_d}}\right) \qquad (4.31)$$

$\boldsymbol{E_b/N_d}$ is the decision variable SNR. This equation relates the probability of error to the decision variable signal instead of the channel signal.

Equation (4.31 can be written as a function of the channel SNR but after adding the oversampling gain which is the number of samples per symbol period.

$$P_e = \frac{1}{2} erfc\left(\sqrt{N\frac{E_b}{N_o}}\right) \tag{4.32}$$

Before the equation (4.32), there were two methods to decrease the probability of error in the received bit stream. The first method is increasing the energy per bit which means more power must be transmitted or lower bit rate should be used. The second method is decreasing the noise power spectrum density which depends on the physical nature of the channel and in many cases it is very difficult to do this.

Now and according to the equation (4.32), there is a third method to increase the signal to noise ratio and decreasing the probability of error. This method is by over sampling the received vector and using more than one sample in the calculation of the decision variable. This method will complicate the calculations in the detection process but it will save the transmitted power and the used bit rate.

The gain in the SNR that is achieved by oversampling the received signal is similar to the process gain that is achieved in DSSS-BPSK system. In DSSS receiver, the decision variable is formed by integrating the received data multiplied by the spreading code. Here the received signal is sampled by the code rate which equals to the spreading rate. The channel noise will be sampled by the same rate, so more than one sample of the noise will be taken during the bit interval if a single noise sample is taken during the chip period. The correlator in the detector will average N samples of the received signals and this will lead to an enhancement of the system performance. The enhancement in performance is due to the averaging of the channel noise samples where the variance of the average is smaller than the variance of the channel noise samples by the process gain.

5 Simulations

The simulation results of the previous researches [1, 2, 3, 4, 5, 6, 7] are not shown here because of two reasons. The first is that most of these researches apply their ideas on the voice and video signals and when we apply them on a noisy BPSK system they gave a little and in some cases no enhancement. The second reason is that these algorithms fall to work if the noise power is high and the SNR is below a certain threshold. On the other hand, our algorithm works for any SNR value and it has a linear SNR gain as show in Section (*5.3*).

The simulation results of the proposed ideas that are discussed in this paper are represented in three subsections. The first subsection discusses the relation between the variance of the white noise and the color noise and how the noise bandwidth affects the value of the noise power and power spectrum density. The second subsection shows the difference between the probability density functions of the channel noise and the decision variable noise. The last section presents the application of the proposed ideas on the well known system which is the binary shift keying system.

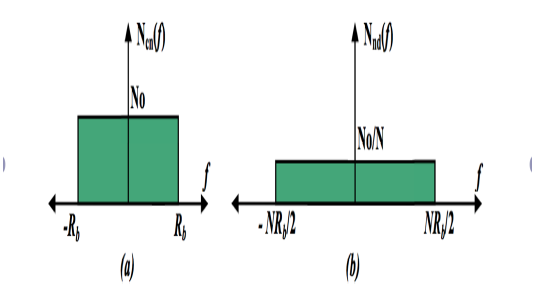

Figure 1: (a) The PSD of the channel noise samples (b) The PSD of the decision variable samples

5.1 Variance of the white noise and the color noise

AAny white noise has a fixed power spectrum density but the power of the white noise is infinity because its bandwidth is infinity. On the other hand, if the channel noise is sampled with a sampling frequency of $\boldsymbol{F_s}$, the noise bandwidth $\boldsymbol{B_{cw}}$ will be bounded by $\boldsymbol{F_i/2}$ as shown in equation (5.33).

$$0 \leq B_{cw} \leq \frac{F_s}{2} \tag{5.33}$$

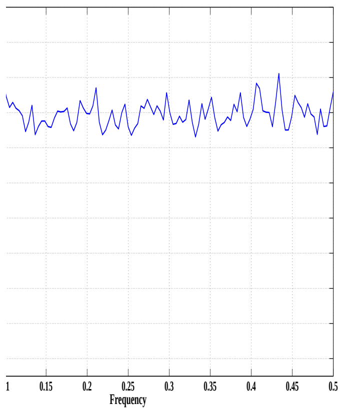

Figure 2: The power spectrum density of the samples of white noise signal

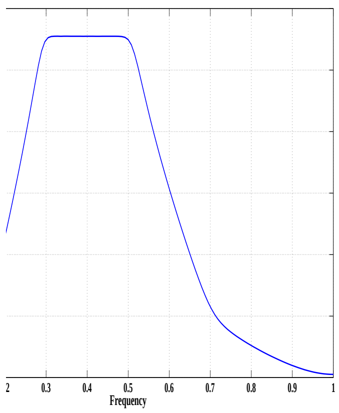

Figure 3: The power spectrum density of the samples of white noise signal

The noise samples of the white noise signal will in this case have a fixed power. The variance of these samples which represents the power of the white noise samples will equal to the power spectrum density of the noise multiplied by the sampling frequency.

$$\sigma_w^2 \quad = \quad 2B_{cw}\frac{N_o}{2} = N_oF_s \tag{5.34}$$

$$\because N_o \quad = \quad \frac{\sigma_w^2}{F_s} \tag{5.35}$$

This is the relation between the white noise power and the power spectrum density which is depending on the sampling frequency. Figure (2) shows the power spectrum density of a vector of 10^6 white noise samples with ***10dB*** variance which is generated using MATLAB.

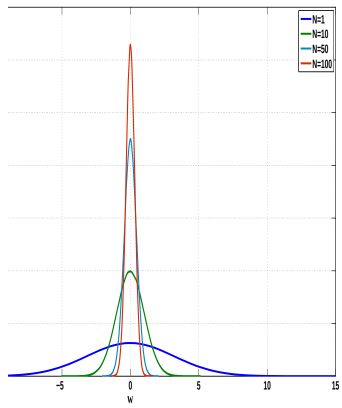

Figure 4: The PDF of the decision variable noise for the case of white Gaussian noise channel

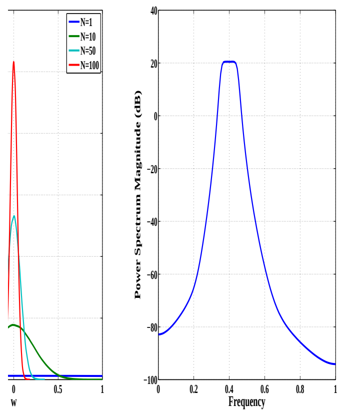

Figure 5: (a) The PDF of the decision variable noise for the case of color Gaussian noise channel (b) The PSD of the used color noise

The noise power spectrum density is a fixed parameter of any communication channel. It is always a constant value according to the noise activities in the channel. On the other hand, the noise samples that are processed by the receiver will have a fixed power which equals to the noise power spectrum density multiplied by the sampling frequency at the input of the receiver as shown by be equation (5.34).

If a color noise with the same power is generated by passing the previous white noise vector through any linear filter, the resultant color noise power spectrum density should be increased as shown in Figure (3) because the noise power is fixed. Here the normalized color noise bandwidth is 0.2.

From the previous figures, due to the fact that

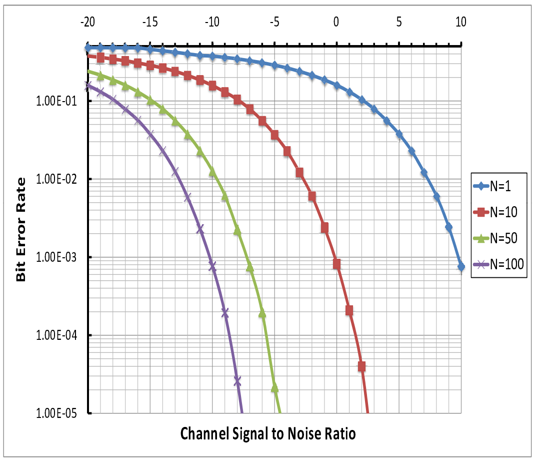

Figure 6: (a) The BER of BPSK detector in WGN channel (b) The BER of BPSK detector in CGN channel

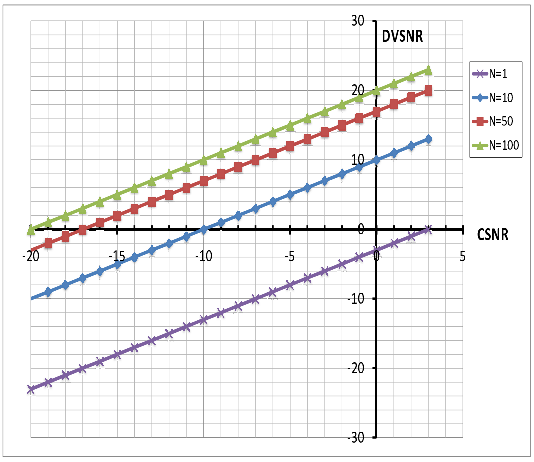

Figure 8: (a) The DVSNR versus the CSNR in WGN channel (b) The DVSNR versus the CSNR in CGN channel

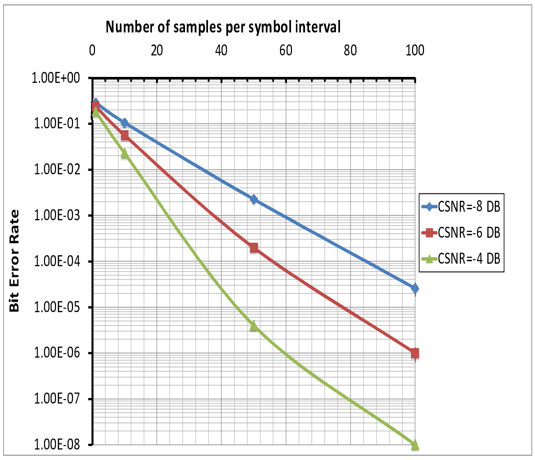

Figure 7: (a) The BER of BPSK detector versus the number of samples in WGN channel (b) The BER of BPSK detector versus the number of samples in CGN channel

the received noise signal has a fixed power spectrum density, the power of the noise will be changed by changing the sampling frequency of the white noise signal or the noise bandwidth of the color noise.

5.2 Probability density functions of the channel noise and the decision variable noise

In this subsection the differences among the PDFs of the noise samples in the decision variable which is formed by averaging of N noise samples are shown for different sampling frequencies. Figure (4) shows the PDFs of the decision variable for the white Gaussian noise channel case with N= 1,10,50, and 100 samples per symbol period. The variance of the noise in the decision variable will be decreased when the number of samples in the symbol period is increased. This result is also achieved with color Gaussian noise channel although the noise samples are correlated. Figure (5(a)) shows the PDFs of the decision variable for color noise channel with N= 1, 10, 50 and 100 samples per symbol period. Figure (5(b)) shows the PSD of this channel noise.

5.3 Probability of error in the BPSK using the new idea

Here the simulation results of the detection of a BPSK signal which is corrupted by a white and color Gaussian noise are represented. In white noise case, the channel signal to noise power ratio (CSNR) is varied from -20 dB to 10 dB but in color noise, the CSNR is varied from -13dB to 9dB. The bit error rate in a vector of 107received binary symbols is calculated each time. Figures (6(a)) and (6(b)) show the bit error rate in the received data vector versus the CSNR for the white and the color noise channel cases respectively. The decision variable of the correlator detector is formed based on the averaging of different numbers of samples per symbol period. The cases of a single received sample, 10 received samples, 50 received samples, and 100 received samples per symbol period are shown in these figures. It is clear that the noise performance is enhanced as the number of samples per symbol period is increased. The rate of performance enhancement in the white noise channel is better than the rate of enhancement in the color noise channel because the color noise samples are correlated.

Figures (7(a)) and (7(b)) show the plot of the bit error rate in the received data versus the number of samples per symbol period at certain channel signal to noise ratio values. These figures show that the performance enhancement is not linear with the number of samples per symbol period. The bit error rate will asymptotically approach to zero as the number of samples per symbol period approaches to infinity which agrees with the theoretical study. Figures (8(a)) and (8(b)) show also the relation between the channel signal to noise ratio (CSNR) and the decision variable signal to noise ratio (DVSNR). Increasing the number of samples in the averaging process to form the decision variable each symbol period will increase the decision variable SNR because the average process will decrease the variance of the noise samples and hence it will decrease the noise power spectrum density.

The increasing in the decision variable SNR in white noise case is greater than the increasing in the decision variable SNR in color noise case for the same reason of the correlation between the noise samples in the color noise case. Also the figure shows that the enhancement in the DVSNR is nonlinear with the increasing of the number of samples in per symbol interval.

6 Conclusion

The noise performance in digital receivers can be enhanced by oversampling the received signal and calculating the time average of the correlator output based on more than one sample in the decision variable. This enhancement can be considered as the oversampling gain effect in the decision variable. The time average will approach to the desired signal value where the noise average will approach to zero. The noise power in the signal bandwidth will be decreased by a factor equals to the number of the samples on the symbol period that will be used in the averaging process. The decrement of the noise power in the decision variable will increase the decision variable signal to noise ratio and this will enhance the system probability of error. This enhancement in the probability of error needs neither more transmitted power nor increasing in the signal bandwidth but only it needs an increase in the processing operations on the receiver. The noise performance enhancement that was discussed in this paper is valid for both white noise and color noise cases where the performance enhancement in the white noise case is greater than the performance enhancement in the color noise case.

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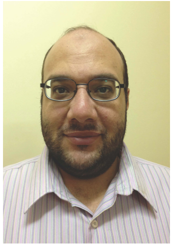

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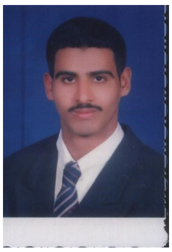

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