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Performance Comparison of DS-CDMA System Using Wavelet Based Shrinkage Methods

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Abstract

Spread spectrum communication, with its unique characteristics and inherent noise cancellation capability becomes an increasingly popular technique for use in many different systems like military applications. In addition to that, Wavelets had been developed and has attracted much attention in signal processing that provides an effective alternative to conventional transforms. A new method for Wavelet denoising, that uses a Wavelet shrinkage estimate via Wiener filtering, is proposed. The main aspect of the proposed method is its use of two Wavelet bases-one for the design of the empirical Wiener filter, and other for its application. In addition to Wavelet denoising, the Wiener filter is used to process the signals corrupted by additive Gaussian noise; i.e., denoising is performed with a Wavelet-based method, and suppressing the coefficients using the Wiener filter approach. The impulse response of the Wiener filter is calculated from the Wavelet transformed coefficients. One of the possible measurements of denoising quality is the mean Bit Error Rate. The simulation of the proposed method shows a low BER for higher values of SNR, than the system that uses conventional shrinkage methods, and the conventional spread spectrum receiver.

Keywords: Denoising, spread spectrum, Bit Error Rate, Wavelets, Wiener filter, Shrinkage

Introduction

CDMA works on the basis of spread spectrum techniques where each user occupies the whole accessible bandwidth [1]. A digital signal is spread (i.e., multiplied by) at the transmitter with the aid of a pseudo-random noise (PN) code [2]. Now days, wavelet transforms have become very effective tool for correlation than the conventional signal transform. Denoising refers to the reduction of noise level by processing the wavelet coefficients. In this paper Double density discrete wavelet transform [3] is used. At each decomposition level threshold have been calculated and soft thresholding is applied. The use of wavelets is to identify the presence of a spread spectrum signal that can increase accuracy. In [4] authors used a new method of denoising in spread spectrum systems in which noisy signal and code are replaced by wavelet coefficients.

In [5] and [6] wavelets for denoising in an attempt to enhance CDMA signal for time delay estimation and code tracking is used. In [7] and [8] wavelets are used to separate CDMA signal from GSM and to identify the CDMA signal is shown. One of the applications of Discrete Wavelet Transform is the denoising process, which attempts to remove the small part of the signal assumed as noise [9]. The signal obtained from the physical environment has contains disturbing noise. And hence, Donoho [10] proposed wavelet denoising steps has applied many one or two dimensional signal after hard or soft thresholding methods. Usually, the noise is modeled as stationary independent zero-mean white Gaussian variables. Reduction of BER is the main target of the research. The Weiner filter adopted by Abd El-Fattah *et al* [11] is cascaded with the Wavelet filter; hence, better BER for the lower SNR values can be obtained when compared to other denoising methods. The use of wavelets is to identify the presence of a spread spectrum signal that can increase accuracy. In [24]authors used a new method of denoising in spread spectrum systems in which noisy signal and code are replaced by wavelet coefficients. The performance of uncoded uplink transmissions in a broadband code division multiple access (CDMA) system using tapped delay line (TDL) antenna array under multipath conditions is investigated [25]. An efficient search algorithm to generate the sub-optimal parameter β for maximizing the carrier-to-interference ratio (CIR) is proposed and the performance of the ICI mitigation for the higher-frequency offset is improved [26].

In this paper, a new wavelet based wiener shrinkage method for signal denoising in spread spectrum communication in the presence of Additive White Gaussian Noise (AWGN) is proposed. Discrete wavelet transform is used for signal decomposition with two sub bands. This paper is organized as follows: In section 2: Work related to this manusript is discussed. In section 3: Overview of 1-D Discrete Wavelet Transform is shown In section 4 and 5: wavelet shrinkage method with hard and soft thresholding techniques used in spread spectrum is discussed. In section 6: proposed denoising method with threshold calculating parameters is given. In section 7: simulation results are discussed. Here, we evaluate the system (BER) performance as a function of energy per bit to noise power spectral density when the various excision techniques are applied to the DSSS prior to the detection. Finally in section 8: Based on the work specified, the conclusions are drawn.

Related Work

Wavelet denoising has found application fields in signal processing recently [12] and [13]. Chen *et al* and Coll *et al* [14 and16] proposed a denoising process to remove the noise while retaining and not distorting the quality of the processed signal [15]. The traditional way of denoising to remove the noise from a signal, is to use a low or band pass filter with cut off frequencies. However, the traditional filtering techniques are able to remove a relevant part of the noise; but they are incapable if the noise is in the band of the signal to be analyzed. Therefore, many denoising techniques are proposed to overcome this problem. Because the origin and non stationarity of the noise infects the signal, it is difficult to model it. Nevertheless, if the noise is assumed as stationary, an empirically recorded signal that is corrupted by additive noise, can be represented as:

$$y(t) = x(t) + \sigma\varepsilon(t), t = 0,1, \dots \dots \dots \dots n - 1 \quad (1)$$

where, $y(t)$ denotes noisy signal, x(t) indicates the noise free actual signal, and $\varepsilon(t)$ are independently normal random variables, and σ represents the intensity of the noise in $y(t)$. The noise is usually modeled as stationary independent zero-mean white Gaussian variables [17]. When this model is used, the objective of noise removal is to reconstruct the original signal $x(t)$ from a finite set of $y(t)$ values, without assuming a particular structure for the signal. The usual approach to noise removal, models the noise as a high frequency signal, added to an original signal. These high frequencies can be brought out, using the traditional Fourier transform, ultimately removing them by adequate filtering. This noise removal technique is conceptually clear and efficient, since it depends only on calculating the DFT [18].

Overview of Discrete Wavelet Transform

D Discrete Wavelet Transform

The analysis filter bank decomposes the input signal into two sub band signals, c(n) and d(n) as shown in Fig.1. The signal c(n) is the low frequency part of the input signal, while the signal d(n) gives the high frequency part of the input signal. The Low pass filter and high pass filters are represented by af1 (analysis filter 1) and af2 (analysis filter 2) respectively. As given in the figure, the output of each filter is down sampled by two, to obtain the two sub band signals c(n) & d(n). The resultant single signal will be a combination of the synthesis filter bank [19] of two sub band signals c(n) & d(n).

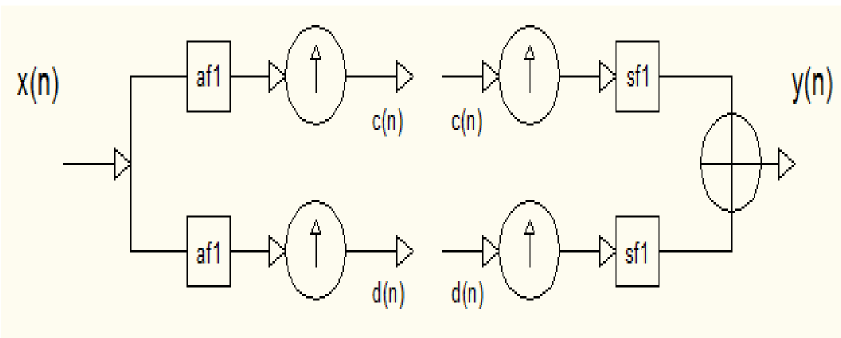

Figure 1: Single level of analysis and synthesis filter bank using the DWT

The synthesis filter bank up-samples each of the two sub band signals. The resultant signals are filtered using a low pass and a high pass filter. The low pass filter is denoted by sf1 (synthesis filter1) and the high pass filter by sf2 (synthesis filter 2). So, the Wavelet shrinkage is a signal estimation technique, which exploits the remarkable abilities of the Wavelet transform for signal compression.

Signal Denoising Algorithm

The conventional CDMA receiver and the system [21] which uses the Wavelet transform for signal denoising has been discussed. From the simulated result, it is found that the Wavelet transform works well with the lower SNR values as it is a very good decorrelator and hence, it is more advantageous than the conventional one. In the Fig.2, a signal is given by y = x + n, where x denotes the unknown noiseless data and n is the White Gaussian Noise with a mean of 0 and a variance of 1. The general task is to obtain a signal $\bar{x}$ that is as close as possible to x.

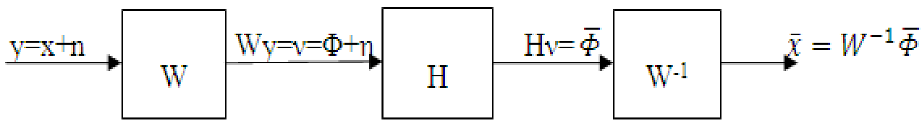

Figure 2: A scheme for classical Wavelet-based denoising

where, W denotes the orthogonal Wavelet transformation, H the thresholding function, and W^{-1} denotes the inverse orthogonal Wavelet transformation.

Wavelet Shrinkage

Wavelet shrinkage can be done in four stages, as illustrated by Robi Polikar [22].

1. *Analysis Filter Bank:*
   - In the first stage, the input data block is analyzed in terms of the DWT. The resulting data are the Wavelet coefficients.
   - The right type of Wavelet needs to be chosen; that is, one that can be accurately reconstructed using the IDWT.

2. *Delay Alignment:*
   - This is a form of phase correction.
   - Low frequencies take a longer time to go through the filter banks than do high frequencies.

3. *Noise reduction stage:*
   - The Minimum threshold is selected for each band. Anything below this threshold value is ignored.

- Low level signals in the transformed sequence could be lost.
- It is assumed that, there is more high frequency noise than low frequency noise.
- The main idea of Wavelet shrinkage is to set the smaller Wavelet coefficients, which are assumed to belong to noise to zero, by applying a non-linear thresholding function, in order to eliminate the noise while preserving the underlying signal.

4. *Synthesis Filter Bank:*
   - In the final stage, the output signal is re-constructed.
   - The IDWT is the complementary half of the Discrete Wavelet Transform DWT.

This section describes the signal denoising algorithm which achieves near optimum soft thresholding in the Wavelet domain. It is used to recover the original signal from the noisy one. The algorithm is computationally more efficient & very simple to implement.

It has the following steps:

Perform single level decomposition of the signal corrupted by the AWGN using the Discrete Wavelet Transform. Estimate the noise variance using σ^2 = MAD(d)/0.6745, where the Median Absolute Deviation of the detail coefficients converges at .6745σ.

- For each sub-band of decomposition, compute the scale parameter.
- For each sub-band,
- Compute the standard deviation σ_y. Compute the threshold, using Eqn (2).
- Apply the soft threshold to the sub band coefficients.

A natural question which arises is, how to choose the thresholding function.

There are several ways to find the threshold:

Universal Threshold

Generally, the threshold can be calculated, using the universal threshold, and it can be given as,

$$T = \sigma\sqrt{2(logN)} \tag{2}$$

where, N denotes the length of the signal, σ implies the estimated noise variance.

It is the desirable threshold in the asymptotic sense, and reduces the cost function of the difference between the functions. If the number of samples is large, the universal threshold gives a good estimate of the soft threshold [10]**.** However, this Wavelet threshold has a fatal shortcoming. Because this threshold value is proportional to the signal size logarithm's square root; therefore, when N is big, the threshold value will tend to reset the Wavelet coefficients, as a result, the Wavelet filter will degenerate as the degradation of low-pass filter. And hence, there is a serious "overkill" Wavelet coefficients tendency.

Due to the above deficiency of Donoho's threshold, the more effective Bayes Wavelet threshold is used, to optimize the performance of the Wavelet threshold denoising algorithm in this study, with the assumption of the Wavelet coefficients obeying a distribution. The threshold, according to the Bayes Rule, is shown by the formula:

$$\lambda_s = \frac{\sigma_D^2}{\sigma} \quad (3)$$

where, λ_s are the various thresholds in various sub bands. σ_D is the noise variance estimation.

Visu Shrinkage

Visu Shrinkage was introduced in [10]. It uses a threshold value, which is proportional to the standard deviation of the noise. It follows the hard thresholding rule. An estimate of the noise level was defined, based on the median absolute deviation given by

$$\hat{\sigma} = \frac{median\left(\left\{\left|d_{i-1,j}\right|: j = 0,1,2,\dots\dots 2^{i-1}-1\right\}\right)}{0.6745} \quad (4)$$

where $d_{i-1,j}$ corresponds to the detail coefficients in the Wavelet transform. Visu Shrink does not deal with minimizing the mean squared error. Another disadvantage is that it cannot remove speckle noise. It can only deal with additive noise. Visu Shrink follows the method of the global thresholding, which is applicable for all the Wavelet coefficients [20].

Thresholding Techniques

In principle, there are two thresholding techniques that are always used in spread spectrum denoising:

Hard Thresholding

Hard Thresholding is a straight forward technique for implementing Wavelet denoising (i.e, 'keep' or 'kill' strategy). If η is the threshold, then the hard thresholding operation on the Wavelet coefficient w_t is given by

$$\delta^H_\eta(w_t) = w_t,\ if\ |w_t| > \eta$$
$$=0, otherwise \quad (5)$$

This operation is not a continuous mapping, and only affects the input coefficients that are less than or equal to the threshold.

Soft Thresholding

The other standard technique for denoising is soft thresholding of the Wavelet coefficient w_t via,

$$\delta^S_\eta(w_t) = sign(w_t)(|w_t| - \eta)_+.$$

$$where,\ sign(w_t) = +1\ if\ w_t > 0,$$
$$= 0\ if\ w_t = 0,$$
$$= -1\ if\ w_t < 0,$$
$$and\ x_+ = x\ if\ x \geq 0, \quad (6)$$
$$= 0\ if\ x < 0.$$

where, sign(w_t) denotes the signum function. Instead of forcing w_t to zero or leaving it untouched, soft thresholding pushes all the coefficients towards zero. And hence, the smoothing effect is better in soft thresholding than in hard thresholding.

Proposed Wavelet Based Wiener Filter For Signal Denoising

The main objective in the reception of a DS-CDMA system is to estimate the symbols which carry the data, but a prerequisite task is to obtain a clean signal by suppressing noise in the received signal. The Wavelet coefficients can be modified based on Wiener shrinkage in the new basis, such that the noise can be removed from the data and its performance compared with several shrinkage methods, for spread spectrum communication.

The popular technique used in many signal enhancement methods is Wiener filter. The Wiener filter is used to obtain a clean signal, corrupted by additive noise. Denoise the signal with a wavelet-based method and suppress the coefficients using wiener filter approach. One of possible measurements of denoising quality is the mean BER.

In general, Wiener filter in the wavelet domain can be given by:

$$h_x(n) = \frac{x^2(n)}{x^2(n) + \sigma^2} \tag{7}$$

where, x(n) are the wavelet coefficients of the signal (s1, . . . , sN). For coefficients, $x^2(n)$ that are large compared to σ^2, $h_x(n) \approx 1$, the Wiener filter offers little gain compared to a hard threshold estimate. On the other hand, coefficients $x^2(n)$ that is small or comparable in size to σ^2 result in $h_x(n) \leq 1$, and contribute the most to the gain in MSE. This is consistent with the fact that the MSE of the Wiener filter.

$$MSE_w = \sigma^2 \sum_{i=1}^{N_s} \frac{x^2(n)}{x^2(n) + \sigma^2} \tag{8}$$

has the highest sensitivity at $x^2(n) = 0$, which decreases monotonically to zero as $x^2(n) \rightarrow 0$ as has been depicted in the literature [23].

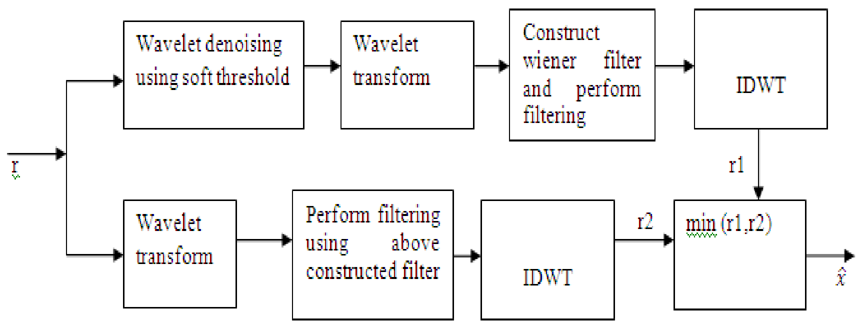

Figure 5: Proposed DS-CDMA Receiver using Wavelet based wiener shrinkage

Fig.5. shows the proposed denoising method- Wavelet based Wiener shrinkage, that can be explained as follows:

In the upper path, the Wavelet transform is used to produce the pilot signal estimate, which is obtained after denoising using soft thresholding approach. This estimate is then used to design an empirical Wiener filter, which is applied to the original noisy signal in the lower path.

1. The incoming noisy signal is Wavelet transformed.
2. The Wavelet coefficients are shrinked using soft thresholding S_T
3. The modified Wavelet coefficients are inverse Wavelet transformed (T_1) to obtain $\hat{x}_1$
4. $\hat{x}_1$ *is* Wavelet transformed (T_2) to obtain $\hat{r}_{21}$.
5. From $\hat{r}_{21}$, the empirical Wiener filter $W_h = \hat{r}_{21}(i)/(\hat{r}_{21}(i) + \sigma^2)$ is constructed.

where, σ^2 can be calculated using σ^2 = MAD(d)/.6745, where the Median Absolute Deviation of the detail coefficients converges at .6745σ.

6. Again the incoming signal is Wavelet transformed (T_2) to obtain the Wavelet coefficients
7. The obtained Wavelet coefficients are filtered with the constructed Wiener filter W_h.
8. The filtered coefficients are inverse Wavelet transformed (T_2^{-1}) seperately to obtain r_1 and r_2 respectively.
9. The output $\hat{x}$ is obtained by finding the minimum of r_1 and r_2.

The choice of T_1 and T_2 is quite insensitive with respect to the final result. To closely resemble the optimal Wiener filter, different type of Wavelet in upper and lower path is used i.e., $T_1 \neq T_2$. In practice, the noise level σ is unknown; so, noise estimation (as described in the appendix1) is needed in a pre-processing step before applying the Wiener shrink. The improved performance obtained by the above procedure is the result of modified Wavelet based Wiener shrink method. The first block of Wavelet transforms, and its inverse corresponds to the Haar Wavelet, whereas the successive block, corresponds to the Daubechies Wavelet. The denoising process consists of the signal Wavelet coefficients, and based on the threshold condition, new coefficients are generated.

An alternative interpretation of the Wiener Shrink is that, classical shrinkage overly shrinks the Wavelet coefficients, thereby resulting in a suboptimal weighting, whereas the Wiener Shrink procedure stretches the shrunk Wavelet coefficients, and brings the coefficients back into the picture, to design an improved weighting profile.

The proposed algorithm is very simple to implement, and computationally more efficient, and it outperforms other thresholding approach like global thresholding.

Results and Discussion

This section presents the results of the computer simulation to evaluate the performance of the proposed signal denoising method in spread spectrum systems. The CDMA signals used in the simulations were generated by the QPSK modulation, and the m-sequence of 4, 8 and 16-bit spreading codes are used for spreading, and the results of the different shrinkage methods are compared. It was observed that the BER decreased with an increasing spreading factor. The processing gain due to the spreading of the data compensates for the noise added in the channel, and hence an increasing spreading factor results in a decreased BER. The demodulated data is compared with the original baseband data to find the total number of errors. Dividing the total number of errors by the total number of demodulated symbols, gives the bit-error-rate.

Performance of the Conventional Wavelet based Wiener Shrinkage

For the Wavelet based Wiener shrinkage, Daubechies Wavelet is used for DWT and single level of decomposition is utilized. The decomposed coefficients are thresholded by the global threshold value, given by Eq. (2). Accordingly, after denoising, the final reconstructed signal output is calculated, followed by a Wiener filter as explained in section 6.4 and decisions about the received symbols are taken by comparing the re-constructed signal with the threshold value. From the simulation,it is seen that a higher spreading factor shows a better performance as compared to the lower one.

Fig. 6. shows the BER performance of the coded DS-CDMA system, using Wiener shrinkage for different processing gains. It is assumed that the receiver has a perfect knowledge of the channel condition.

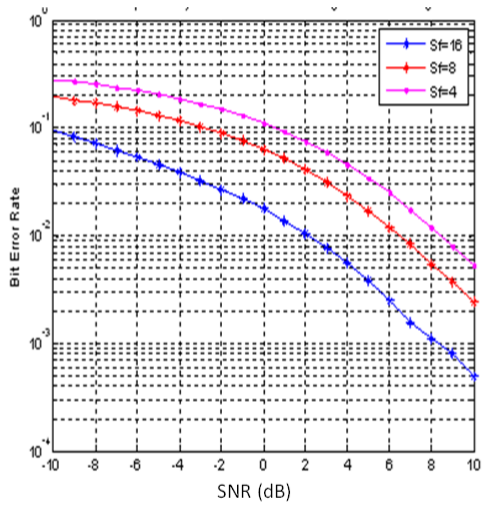

Figure 6: BER vs SNR performance of the conventional Wavelet based Wiener shrinkage

The results are shown by considering the effect of the Wiener shrinkage in the presence of the AWGN with a BER of 10^{-2}, $0.4*10^{-2}$ and $0.15*10^{-2}$ for 2 dB, 4 dB and 6 dB respectively, for a processing gain of 16. For the processing gain of 8, the BER will be increased as $0.3*10^{-1}$, $0.1*10^{-1}$ and 10^{-2} correspondingly for the same SNR values. Hence, for the same values of SNR, the BER is decreased to an extent for the spreading factor of 16, when compared to the spreading factor of 8.

Performance of the Wavelet shrinkage

Fig.7. shows the BER performance for the coded DS-CDMA system, using the Wavelet shrinkage in the presence of the AWGN channel.

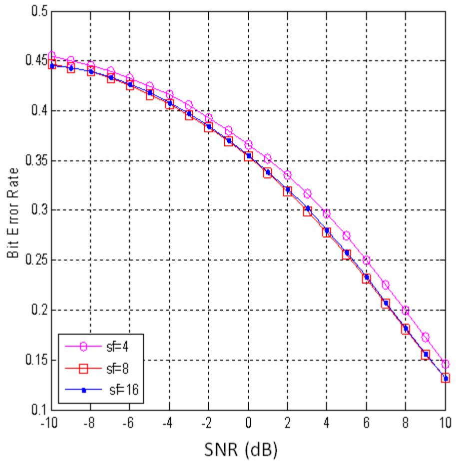

Figure 7: BER vs SNR performance of the Wavelet shrinkage

The performance has been shown by considering the effect of the Wavelet shrinkage for different processing gains, with a BER of 0.4, 0.32 and 0.25 for -3 dB, 2 dB and 5 dB respectively, for a processing gain of 16. Almost the same value of BER is obtained for the spreading factor of 8. Correspondingly, for the processing gain of 4, the BER will be increased gradually for all SNR values.

In this simulation, the BER performance for different values of the channel SNR was studied. The simulation was run for ten values of SNR in dB, with three different spreading factors and for 4 users. It is clearly seen that the BER decreases with increasing SNR, which is consistent with the theory. So, when the Wavelet shrinkage alone is used, the BER decreases to a certain level, but when the Wavelet filter is used with the Wiener shrinkage, as seen in Fig. 5, the BER is decreased.

Performance of DS-CDMA based on the Visu Shrink Method

Fig.8. shows the BER performance for the coded DS-CDMA system, using Visu shrink, as explained in the previous section for different processing gains. The simulation was run for a range of -10 to 5 SNR in dB versus BER.

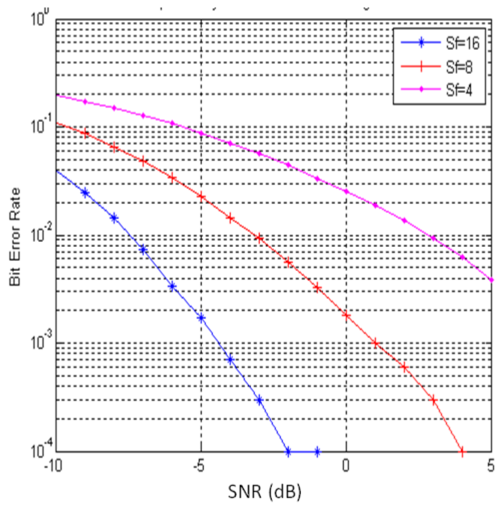

Figure 8: BER vs SNR of DS-CDMA based on the Visu shrink method

The results are shown by considering the effect of the Visu shrink in the presence of AWGN with a BER of $0.3*10^{-1}$, $0.1*10^{-2}$ and 10^{-4} for -10 dB, -5 dB and -2 dB respectively, for a processing gain of 16. For the processing gains of 8 and 4, the BER will be increased correspondingly with respect to the same SNR values. For example, at the BER of 10^{-4}, E_b/N_o for processing gain of 16 is -2 dB and for the spreading factor of 8, E_b/N_o is 4 dB and so, 6 dB improvement is achieved if the spreading factor increases from 8 to 16.

Performance of DS-CDMA for the proposed Wavelet based Wiener Shrinkage
Table 1 shows the simulation conditions of the proposed method, where the QPSK modulation is used with one transmit and receive antenna under the AWGN channel for a maximum of 4 users. The spreading code used for simulation is the Walsh Hadamard code with different spreading codes of lengths 4, 8 and 16.

Table 1: Simulation Conditions

Communication system	DS-CDMA
Modulation	QPSK
Spread code	Walsh- Hadamard code, Length = 4,8,16,32 & 64
Number of Transmitting & Receiving antenna	One each
Channel condition	AWGN
Number of Users	4

Fig.9. shows the BER performance of the coded DS-CDMA system, for the proposed Wavelet based Wiener shrinkage in the presence of the Gaussian channel.

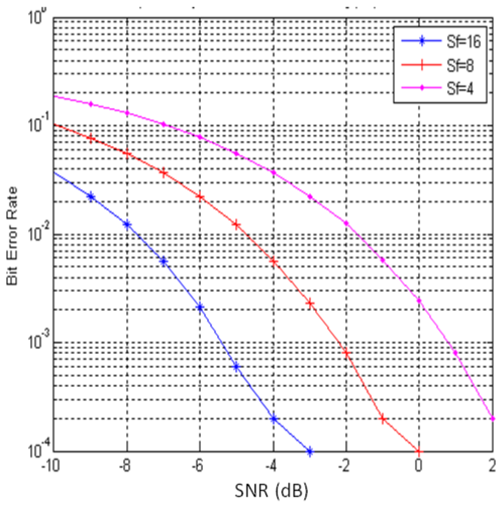

Figure 9: BER vs SNR of DS-CDMA for the proposed Wavelet based Wiener shrinkage

The performance has been shown by considering the effect of the proposed method for different processing gains with a BER of 10^{-2}, $0.1*10^{-2}$ and $0.1*10^{-3}$ for -8 dB, -6 dB and -4 dB respectively, for a processing gain of 16, whereas the same BER is obtained for -6 dB, -3 dB and -1 dB respectively, for the spreading factor of 8, and -2 dB, 0 dB and 2 dB for the spreading factor of 4. Hence, 3dB SNR improvement is obtained between the spreading factors of 16 and 8, whereas 6 dB SNR improvement is obtained between spreading factors of 16 and 4 at the BER of $0.1*10^{-2}$.

The performance of the proposed algorithm is very close, and in some cases even more advanced, to that of the already published shrinkage methods. The simulation result shows that the traditional signal denoise methods find it difficult to preserve the details of the signals effectively, while removing the noise. From the figures, it is clear that varying the processing gain has a significant influence on the BER performance, using the shrinkage methods. From the simulation, it is observed that the proposed method of denoising is better than the other methods.

Tables 2 and 3 show the results of the existing denoising methods like the Wavelet, Visu, Wiener shrinkage and the proposed denoising scheme.

Table 2: Bit Error rate for different dB values of the Wiener and Wavelet shrinkage

	BER values of Wiener shrink			*BER values of Wavelet shrink*		
SNR	*Sf=4*	*Sf=8*	*Sf=16*	*Sf=4*	*Sf=8*	*Sf=16*
-10	0.2807	0.1953	.0948	0.4544	0.4472	0.4454
-9	0.2682	0.1829	0.0829	0.4508	0.4435	0.4432
-8	0.2542	0.1702	0.0720	0.4460	0.4392	0.4392
-7	0.2386	0.1569	0.0623	0.4402	0.4327	0.4336
-6	0.2226	0.1440	0.0537	0.4333	0.4253	0.4267
-5	0.2055	0.1301	0.0458	0.4251	0.4168	0.4183

-4	0.1868	0.1165	0.0387	0.4159	0.4070	0.4087
-3	0.1681	0.1028	0.0323	0.4054	0.3956	0.3975
-2	0.1490	0.0899	0.0270	0.3934	0.3834	0.3845
-1	0.1298	0.0761	0.0220	0.3806	0.3699	0.3711
0	0.1105	0.0637	0.0177	0.3662	0.3548	0.3558
1	0.0929	0.0518	0.0137	0.3517	0.3384	0.3396
2	0.0753	0.0408	0.0104	0.3352	0.3197	0.3215
3	0.0592	0.0313	0.0077	0.3170	0.2999	0.3025
4	0.0459	0.0233	0.0056	0.2968	0.2786	0.2808
5	0.0341	0.0169	0.0038	0.2743	0.2560	0.2580
6	0.0250	0.0119	0.0025	0.2504	0.2315	0.2338
7	0.0173	0.0084	0.0016	0.2255	0.2072	0.2084
8	0.0119	0.0055	0.0011	0.1998	0.1817	0.1826
9	0.0080	0.0037	0.0008	0.1726	0.1560	0.1570
10	0.0053	0.0024	0.0005	0.1458	0.1318	0.1318

From the Table 2, it is found that a BER of .0024 is obtained for 10 dB for the spreading factor of 8, whereas the same BER is obtained for 6 dB in the case of 16 as the spreading factor. So, 4 dB improvements in SNR are obtained, when the Wiener shrinkage is used. While using the Wavelet shrinkage, the BER is almost the same for all spreading factors.

And it is found that all the BER values for different processing gains are higher, than that obtained by the Wiener shrinkage. It is observed further that noise can be reduced to a very low level, when compared to the conventional system and without the Wiener filter**.** The resulting plot shows that the BER decreases with decreasing number of interferers. Further, the BER values corresponding to SNR = 5 dB were lower than the BER values corresponding to SNR= 0 dB. The results are consistent with the theory.

Table 3: Bit Error rate for different dB values of the Visu shrink and the proposed method

SNR	*BER values of Visu shrink*			*BER values of proposed*		
	Sf=4	*Sf=8*	*Sf=16*	*Sf=4*	*Sf=8*	*Sf=16*
-10	0.1967	0.1090	0.0394	0.1851	0.1023	0.0367
-9	0.1728	0.0864	0.0246	0.1567	0.0769	0.0223
-8	0.1499	0.0657	0.0143	0.1293	0.0550	0.0121
-7	0.1287	0.0477	0.0073	0.1030	0.0367	0.0056
-6	0.1073	0.0337	0.0034	0.0780	0.0222	0.0021
-5	0.0882	0.0227	0.0017	0.0552	0.0121	0.0006
-4	0.0712	0.0144	0.0007	0.0365	0.0056	0.0002
-3	0.0567	0.0094	0.0003	0.0222	0.0023	0
-2	0.0440	0.0056	0.0001	0.0125	0.0008	0
-1	0.0334	0.0033	0.0001	0.0058	0.0002	0

0	0.0252	0.0018	0	0.0024	0	0
1	0.0188	0.0010	0	0.0008	0	0
2	0.0137	0.0006	0	0.0002	0	0
3	0.0093	0.0003	0	0	0	0
4	0.0063	0.0001	0	0	0	0
5	0.0038	0	0	0	0	0

From the Table 3, it is shown that, in the presence of the Visu shrink, a BER of 0.0003 is achieved for the SNR value of 3 dB, using the spreading factor of 8, whereas for the same BER with the spreading factor of 16, the SNR value obtained is -4 dB. And hence, 6 dB improvements in SNR are obtained. This improvement is due to the increase in the processing gain.

Similarly, in the proposed method, a BER of 0.0002 is achieved for the SNR value of 2dB,-1dB and -4 dB for the processing gains of 4, 8 and 16 respectively. And after the BER of 0.0002, the BER becomes zero. The SNR value obtained is -2 dB. And hence, 3 dB improvements in the SNR are obtained. This improvement is also due to the same reason mentioned above.

Conclusions

In this paper, a new scheme for Wavelet denoising of signals, i.e., a hybrid of standard thresholding and empirical Wiener techniques for different processing gains is proposed. The resulting cooperation creates a Wavelet-domain filter close to the optimal Wiener filter, while the Wiener Shrinkage requires the calculation of two Wavelet transforms, the increase in performance should outweigh the slight increase in computational complexity. It is emphasized, that the performance is compared with the Wavelet shrinkage using the soft threshold, Wavelet based Wiener shrink and Visu shrink. From the comparison, it is seen that the proposed method outperforms the other shrinkage methods.

Current research is directed at an analysis of the choice of Wavelets in the upper and lower paths in the hybrid scheme. In particular, it is necessary to understand how their mismatch affects the performance of the algorithm.

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