Narrowband Interference Suppression in CDMA using Random Walk Tracking Algorithm

S. Mohammad Saberali 1, 2; Hamidreza Amindavar 1
1. Department of Electrical Engineering, Amirkabir University of Technology, Tehran, Iran, 15914
2. Iran Telecommunication Research Center

Abstract

It has been shown that the narrowband interference suppression capability of a direct sequence spread spectrum system can be enhanced considerably by processing the received signal via a prediction error filter prior to correlating it with the Pseudo Noise (PN) sequence. In this paper we present a new method to suppress narrowband interference in Direct Sequence Code Division Multiple Access (DS-CDMA) systems. The proposed scheme is a nonlinear predictor that consists of a quantizer and random walk tracking algorithm. This algorithm is used for tracking a random walk in white Gaussian noise. This algorithm has two important features. First, this algorithm does not require the estimation of the interference statistics. Second, it does not require training sequences. Computer simulation results show that the proposed approach has better performance than conventional linear filtering.

1. Introduction

Communication networks involving the overlay of spread spectrum systems on narrowband services are of increasing attention as a mean of producing great efficiencies in the use of radio spectrum. At the spread spectrum receiver, the received signal includes the spread spectrum signal, narrowband interference from other communication systems and noise.

Although direct sequence spread spectrum techniques offer an inherent capability of rejecting narrowband interference, their performance in the presence of such interference can be significantly enhanced by processing the received signal prior to correlating it with PN sequence. In a DS-CDMA system each user has a distinct PN sequence. The message from each user is modulated with the corresponding PN sequence, thus there is a direct sequence spread spectrum for each of them. Therefore the performance of CDMA systems can be improved too, if appropriate narrowband interference suppression techniques are employed prior to despreading. This improvement allows a CDMA system to have more users, i.e. the capacity of the system will increase. Narrowband interference suppression techniques are based on the idea that the spread spectrum signal, having a nearly flat spectrum, can’t be predicted accurately from its past values while narrowband interference can be predicted more accurately. Hence a prediction of the received signal based on previously received values will, in effect, be a prediction of interfering signal. This prediction of the interference can be subtracted from the received signal before it is sent to the correlator for despreading. In the past, several linear prediction techniques were used for narrowband interference suppression in DS spread spectrum [1]. Since the DS signal, which can be modeled as identically independent distributed (i.i.d.) binary sequence, is non-Gaussian, the optimal filter in this case is nonlinear. Nonlinear sub-optimal techniques for narrowband interference suppression in spread spectrum systems are presented in [2] and [3]. They proposed nonlinear Approximate Conditional Mean (ACM) filter of the Masreliez type and obtained significantly better results than linear methods when the statistics of interference is unknown. These filters were proposed for non-Gaussian detection problems [4]. The nonlinearities in the ACM filter take the form of a soft decision feedback which seeks to remove the spread spectrum signal from the estimation of the narrowband interference.

In practice, the parameters of the interference are rarely known to the receiver. Also, the interference can have statistics that vary with time. An effective suppression technique in this case is one that can adapt itself to variations in the interference statistics. Therefore, when the statistics of the narrowband interference is unknown or time varying, adaptive techniques must be used. In this context LMS algorithm is one of the simplest adaptive algorithms to analyze and implement that can be used as a linear predictor. In [2] and [3] the soft decision feedback was incorporated into an LMS adaptive filter. The proposed nonlinear adaptive algorithm of [2] and [3] shows a significant improvement over existing linear filters. However their complexity is too high to be acceptable for practical applications. Another drawback of their adaptive nonlinear filter is its slow convergence rate. These filters converge approximately after 500 iterations [2].

In this paper we use random walk tracking algorithm for tracking narrowband interference with unknown statistics. This algorithm tracks narrowband interference without need to training sequences. In [6] and [7] a simple quantizer is used as a hard decision device for estimating spread spectrum signal. We use this approach for improving the results obtained by random walk tracking algorithm.
2. Random Walk Tracking Algorithm

This algorithm is used for tracking a random walk in Gaussian observation noise when the walk increment is unknown [5]. The estimator is the mean of the noisy observations on a window of some length. The algorithm approximates the optimal window which minimizes the Mean Square Error.

A d-dimensional random walk with noisy observations is modeled as below

\[ \theta_{i+1} = \theta_i + \gamma \omega_i \]

\[ y_i = \theta_i + e_i \]

where \( \gamma \) is a scalar, \( \omega_i \) and \( e_i \) are white noise processes, mutually independent, with covariance matrices respectively equal to \( I \) and \( \sigma^2 \). The parameter \( \gamma \) is assumed to be unknown.

At each time \( t \), the sequence of estimators is defined on a window of length \( m, m_0 \geq 1 \) by

\[ \hat{\theta}_i = \frac{1}{m} \sum_{k=i-m+1}^{i} y_k, \quad i = 0, \ldots, \lfloor \log_2 \frac{t}{m_0} \rfloor \]  

(3)

The best estimator is one that minimizes the Mean Square Error:

\[ E \left\| \hat{\theta}_i^{(t)} - \theta_i \right\|_2^2 \]

(4)

where \( \|x\|_2 \) is the Euclidean norm of \( x \).

In [5] the following equation is obtained for the Mean Square Error

\[ E \left\| \hat{\theta}_i^{(t)} - \theta_i \right\|_2^2 = \sigma_i^2 + b_i^2 \]

(5)

where \( \sigma_i^2 \) and \( b_i^2 \) are defined as:

\[ \sigma_i^2 = \frac{\sigma^2 d}{m} \]

(6)

\[ b_i^2 = \frac{\gamma^2 d (m_i - 1)(2m_i - 1)}{6} \]

(7)

It is easy to show that \( \sigma_i^2 \) is a decreasing function of \( i \) and \( b_i^2 \) an increasing function. Thus the optimal window is the window which balances \( \sigma_i \) and \( b_i \). The optimal length is one that verifies the equivalence:

\[ m^* = \max \left( 1, \frac{\sigma_i}{\gamma} \right) \]

(8)

As the parameter \( \gamma \) is unknown a direct computation of \( m^* \) is not possible. Random walk tracking algorithm is used to find this optimal length without a priori knowledge on the value of \( \gamma \) [5]. This algorithm is represented in Fig. 1. In this figure \( k \sigma \) is the confidence region of \( \hat{\theta}_i^{(t)} \) and \( k \) is a constant suitably chosen.

3. New Nonlinear Algorithm for NBI Suppression

We follow the model described in [2]. In particular, we assume that the received signal consists of spread spectrum signal, the narrowband interference and the white Gaussian noise. We further assume that the received signal is sampled at the chip rate of the PN sequence. We thus have
\[ z_k = s_k + i_k + n_k \]  
(9)

where \( s_k \), \( i_k \) and \( n_k \) are samples of spread spectrum signal, narrowband interference and white noise respectively.

As in [2], the spread spectrum signal \( s_k \) is the sum of \( N \) i.i.d binary random variable, where \( N \) is the number of active users in CDMA system. This is so, since the user message and the PN sequence are assumed purely random. It is also assumed that each user is received at the same (normalized) power. Thus all possible values of \( s_k \) are from \( \{-N, -N+2, \ldots, N-2, N\} \).

In [6] and [7] a new reduced complexity nonlinear technique is proposed for narrowband interference suppression in CDMA. We use this approach for improving the performance of random walk tracking algorithm. Fig. 2 shows the block diagram of our scheme. Assume that random walk tracking algorithm can generate a good estimate of narrowband interference, i.e. \( \hat{z}_k \cong i_k \).

Then the quantizer’s inputs can be expressed as
\[ q_k = z_k - \hat{z}_k = s_k + i_k + n_k - \hat{z}_k \cong s_k + n_k \]  
(10)

If the amplitude of the channel noise \( n_k \) is smaller than the quantization step, the quantizer’s outputs should be equal to the spread spectrum signal, i.e. \( \hat{s}_k = s_k \). We saw in the previous paragraphs that all possible values of \( s_k \) are \( N+1 \), so an \((N+1)\)-level quantizer is enough for its decision. If we subtract \( \hat{s}_k \) from \( z_k \), we obtain
\[ \tilde{z}_k = z_k - \hat{s}_k = s_k + i_k + n_k - \hat{s}_k = i_k + n_k \]  
(11)

By this approach we see that \( \tilde{z}_k \) is composed of narrowband interference, additive white Gaussian noise and the spread spectrum signal is removed. Therefore in estimating interference non Gaussian signal is vanished and the random walk tracking algorithm operates in a Gaussian environment, and thus could have better prediction results for narrowband interference suppression. Like the predictors in [2] and [7] the proposed algorithm will generate a biased estimate of the spread spectrum signal. Once the offset is removed, the system should continue to make good estimates of the spread spectrum signal. As in [7] we estimate the offset parameter \( d_k \) iteratively, and then we subtract it from our estimate of interference to alleviate the offset problem.

4. Simulation Results

Computer simulations were carried out to evaluate the performance of the nonlinear random walk tracking algorithm. The metric we use for comparing the algorithms is the SNR improvement defined in [2] and [3] and given by
\[ \text{SNR improvement} = \frac{E(|z_k - s_k|^2)}{E(|\varepsilon_k - s_k|^2)} \]  
(12)

where \( \varepsilon_k \) is the output of the filter, i.e. the received signal less the estimate of the interference. This equation represents the gain in suppressing the interference and is defined as the ratio of the SNR at the filter output to the SNR at the filter input. Input and output SNRs are given by
\[ \text{SNR at the filter input} = \frac{E(s_k^2)}{E(|z_k - s_k|^2)} \]  
(13)
\[ \text{SNR at the filter output} = \frac{E(s_k^2)}{E(|\varepsilon_k - s_k|^2)} \]  
(14)

as in [2] the interfering signal is obtained by passing white noise through a second order IIR filter with both poles at \( z = 0.99 \), i.e.,
\[ i_k = 1.98i_{k-1} - 0.9801i_{k-2} + w_k \]  
(15)
where $w_k$ is a white Gaussian process. Following [2], the variance of AWGN is $\sigma_n^2 = 1$ and the power of each user’s spread spectrum signal 1. The SNR at the input is varied by changing the power of interfering signal. The total power of noise and interference was varied from 5 dB to 20 dB (All relative to unity power spread spectrum signals). Figs. 3-4 show the simulation results for some cases. The simulations were run for 1000 data points and the average SNR improvement over these points is calculated. In [2] they allow the adaptive algorithm converges and they calculate the average on the last 500 points. Because random walk tracking algorithm does not require training sequence, the tracking is achieved from the first point, and the results are averaged over all the points. Simulation results show that the proposed approach has better performance than conventional linear filtering.

5. Conclusion

A new algorithm has been proposed to suppress narrowband interference in a DS-CDMA system. Then a nonlinear predictor with offset compensation is used to improve the performance of the algorithm. The main idea of this approach is the introduction of a new low complexity algorithm that can track the narrowband interference when the statistics of interference is unknown or time varying. One feature of this algorithm is that it does not require the estimation of interference statistics. The other feature is that it does not require training sequence.

References


