SUPPRESSION OF NARROW-BAND INTERFERENCE IN CDMA CELLULAR RADIO TELEPHONE USING HIGHER ORDER STATISTICS

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الخلاصـة :

نَعرِضُ في هذا البحث أداء تقنية الوصول الترميزية المتعددة (CDMA) في الاتصالات اللاسلكية وذلك في حالة استخدام مانع التداخل لإزالة التداخل ذي النطاق الضيق. ويتكون مانع التداخل هذا من مرشح متكيِّف مستعرض ذي معاملات يتم تحديدها بالتنبؤ الخطي وخوارزمية (أقل متوسط كروتس) المبنية على الإحصائيات عالية الرُّتبة (HOS).

تُعتبر خوارزمية أقل متوسط كروتس شديدة الاستجابة للقيم العالية في أخطاء التنبؤ مما يخرج الخوارزمية عن حالة الثبات مالم يتم استعمال مقدار صغير للكسب. وفي هذه الدراسة نبيِّن أولاً، أنَّ خوارزمية أقل متوسط كروتس يمكن بسهولة معاينتها على أنها خوارزمية أقل متوسط تربيعي يُتحكم في مقدار خطواتها بواسطة مربع خطأ التنبؤ ومقدار التباين. ثانيا تم إجراء تعديل على خوارزمية أقل متوسط كروتس، وينطوي هذا التعديل على استبدال مقدار الخطوة المتغيرة بأخرى مثبتة للتأكد من أن متوسط معدل الخطأ التربيعي للخوارزمية يبقى محصورا. كما أبرزت نتائج المحاكاة مدى تأثير استخدام المرشح المتكيف في الحدِّ من ظاهرة التداخل ذي النطاق الضيق في أنظمة الطيف المنتشر وكذلك تم اختبار سرعة الوصول للمعاملات الصحيحة وتحسن نسبة الإشارة للضوضاء ومعدل الخطأ في النبضات للمرشح المتكيف المبني على خوارزمية أقل متوسط كروتس كما تمت المقارنة مع نتائج المرشح المتكيف التقليدي المبني على خوارزمية أقل متوسط تربيعي.

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ABSTRACT

In this paper, the performance of a Code Division Multiple Access (CDMA) cellular communication system in the presence of narrowband interference is investigated when an interference canceller is employed. The interference canceller consists of an adaptive transversal filter whose coefficients are determined by using linear prediction and the least mean kurtosis (LMK) algorithm, which is an adaptive algorithm based on higher order statistics (HOS).

The standard LMK algorithm is very responsive to large values of prediction errors; it may quickly become unstable unless a very small adaptation gain parameter is employed. In this study, we first show that the LMK algorithm can simply be viewed as a variable step size least-mean square (LMS) algorithm where the step size adjustment is controlled by the square of prediction error and its variance. Second, we provide a modification to the LMK algorithm to ensure that the mean-square error of the algorithm remains bounded. Simulation results are presented to demonstrate the effectiveness of the use of such an adaptive filter in mitigating narrowband interference in direct sequence spread spectrum (DS-SS) systems. Speed of convergence, signal-to-noise ratio improvement (SNRI), and error rate performance of a receiver that employs the modified LMK algorithm are examined. In addition, the results obtained by the modified LMK algorithm are compared with the results obtained by the commonly-used LMS algorithm.

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1. INTRODUCTION

Code-division multiple-access implemented with direct-sequence spread spectrum (SS CDMA) signaling is among the most promising technologies for cellular telecommunications services, such as personal communications, mobile telephony, and indoor-wireless networks [1–3]. The advantages of direct-sequence spread spectrum techniques for these services include superior operation in multipath environments, flexibility in the allocation of channels, the ability to operate synchronously, privacy, and increased capacity in burst or fading channels. Also among the attractive features of SS CDMA is the ability of spread spectrum systems to share bandwidth with narrowband communication systems without undue degradation of either system's performance.

The processing gain of a direct sequence SS system provides some degree of protection against narrowband interference (NBI). When the processing gain does not provide sufficient improvement due to bandwidth restriction, the performance of the system can be further improved by using some form of interference rejection. The most techniques used for NBI rejection are provided by using adaptive transversal filter. Not only does active suppression improve error-rate performance, but it also leads to increased CDMA cellular system capacity [2].

An excellent review of interference suppression methods developed prior to 1988 can be found in a survey paper authored by Milstein [4]. A number of authors have explored the performance of such narrowband interference suppression filters for spread spectrum communications signals. These studies have concentrated on quantifying a SNRI at the filter output and have also obtained the bit-error-rate (BER) performance by using tone interference [5], and for order one autoregressive (AR) interference [6]. Fixed and adaptive linear prediction filters were first used to suppress significant portions of the interference. Interpolating linear filters were found to give even greater interference suppression [5–7].

In 1991, Vijayan and Poor proposed nonlinear methods of predicting the narrowband signal that led to significant improvement in the SNR due to filtering [8]. This nonlinear method was derived from a system model that takes into account the non-Gaussian distribution of the observation noise (from the point of view of predicting the interferer, the observation noise consists of additive white Gaussian noise (AWGN) plus the data signal). The nonlinear filter effectively introduces soft decision feedback into conventional filtering, essentially removing the data signal, and reducing the filter adaptation to one in Gaussian white noise. Results were extended to environments with impulsive noise [9].

An overview of the nonlinear methods of predicting the interference is presented by Poor and Ruch [10]. This review paper addressed also the situation in which the NBI is a digital communication signal. In this case, multiusers detection techniques [11] can be used to give quite significant improvement in performance.

A more recent survey of interference rejection techniques is that by Laster and Reed [12]. This paper has surveyed advances in NBI rejection for DS systems, wideband interference rejection for CDMA systems, and interference rejection for frequency hopping systems. Another very recent nonlinear method for NBI rejection is proposed by Krishnamurthy [27], and combines a recursive hidden Markov model estimator, Kalman filter, and the recursive expectation maximization algorithm.

Almost all of the existing adaptive filtering algorithms operate by iteratively minimizing a mean-squared error cost function, due to the mathematical ease it provides. The most common algorithms used in practice are the LMS algorithm and its derivatives [13]. A new fourth order statistics-based adaptive interference canceller is introduced by Shin and Nikias [14] to mitigate interference in environments when a reference signal which is highly correlated with the interference is available.

This paper will consider the suppression of NBI in the case of multiple users served by a CDMA network operating over a multipath Rayleigh fading channel when no reference signal is available. A transversal filter will be introduced in the CDMA receiver. Such a filter forms a linear prediction based on a fixed number of past samples. This estimate is subtracted from the received signal to obtain the error signal. The filter coefficients are determined adaptively using the recently introduced LMK algorithm. This algorithm is a stochastic gradient approach, which minimizes a cost function defined in terms of fourth-order statistics. The algorithm is simple to implement and is applicable to a wide range of adaptive filtering problems. Furthermore, it has been found to be noise-robust to a large class of noise signals such as impulsive, periodic, uniformly distributed, Gaussian distributed, *etc.* [15]. An investigation of an LMK algorithm-based transversal filter is also addressed to suppress NBI in a CDMA system operating in a cellular radio environment. This investigation is based on computer simulation results of the SNRI, BER, and system mismatch (SM). These performance measures have been calculated for two models of interference: namely, multitone and autoregressive interferences, with a wide range of values for the system parameters. These parameters included processing gain, filter length, number of active users of the CDMA, interference power-to-signal ratio (*J/S*), number of tones and interference bandwidth. Moreover, these new results of LMK filter are compared with those using second order statistics, *i.e.*, LMS filter.

2. SYSTEM AND CHANNEL MODEL

Consider a CDMA system operating in a cellular radio channel as shown in Figure 1.

Let K denote the number of active users. The transmitted signal from the kth user in a CDMA system takes the form:

$$S_k(t) = \sqrt{2P}\, b_k(t) c_k(t) \cos[\, \omega_0 t + \phi_k\,] \tag{1}$$

where:
- P, ω_o are the transmitter power and carrier frequency,
- ϕ_k is the phase angle introduced by the kth PSK modulator,
- $b_k(t)$ is the kth source information sequence with rate $1/T_b$,
- $c_k(t)$ is the spreading sequence with a rate $1/T_c$,

Each data bit has a duration of T_b seconds, while the chip of the spreading sequence has duration T_c seconds, and the processing gain is defined as $G = T_b / T_c$. Therefore, the spread spectrum system bandwidth (B_s) equals $2T_c^{-1}$.

We assume that the channel between the kth transmitter and the corresponding receiver at a base station is a frequency nonselective Rayleigh fading channel, and is characterized by three random variables, β_k, τ_k, and μ_k, which are respectively, defined as the gain, delay, and phase of the kth signal at the receiver. The gain β_k is an independent Rayleigh random variable with parameter $\rho = \rho_k = E[\beta_k^2]/2$ for all k, while the delay τ_k,also independent for each signal, has a uniform distribution in [0, T_b]. Further, we assume that the phase μ_k is an independent random variable, uniformly distributed in [0,2π]. For k CDMA users, the received signal $R(t)$ consists of the independently fading CDMA signals, the interfering narrowband $I(t)$, and the thermal noise $N(t)$. That is,

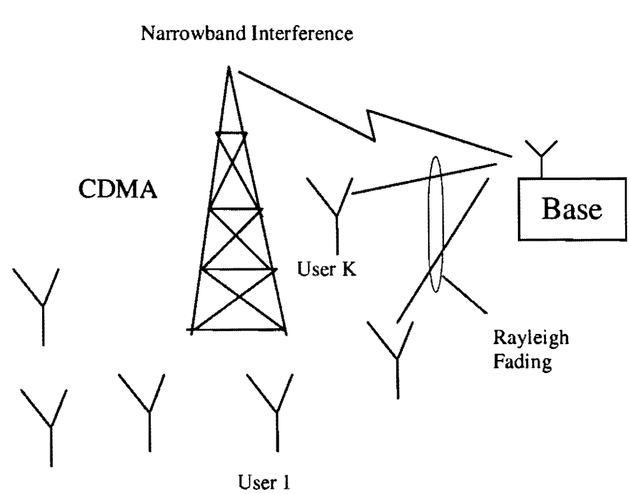

Figure 1. A CDMA environment with multiple users and fading channel.

$$R(t)=\sum_{k=1}^{K}[\beta_k S_k(t-\tau_k)]+I(t)+N(t)\,, \tag{2}$$

where $N(t)$ is additive white Gaussian noise with a two-sided power density $N_o/2$. At the receiver, as shown in Figure 2, the CDMA signal is coherently demodulated, sampled at the chip rate $1/T_c$, filtered, and then despread, to produce the decision statistic. Without loss of generality, we assume that user 1 is the reference user. We, thus, have:

$$R_n=F_n+I_n+N_n\ , \tag{3}$$

where $\{F_n\}$, $\{I_n\}$, and $\{N_n\}$ are the discrete-time sequences from $F(t)=\sum_{k=1}^{K}\beta_k S_k(t-\tau_k)$, $I(t)$, and $N(t)$ respectively.

This study considers two types of narrowband interference; namely Multitone interference and Autoregressive (AR) interference. The modeling of these two interference signals is discussed below.

2.1. Multitone Interference

This signal is modeled as a sum of sinusoids, *i.e.*, $I(n)$ is expressed as:

$$I(n)=\sum_{m=1}^{Q}A_m\cos(2\pi f_m n+\phi_m)\ , \tag{4}$$

where the amplitudes $\{A_m\}$ are selected to be identical, the phases are uniformly distributed on $(0,2\pi)$, and $\{Q\}$ is the number of tones. The autocorrelation function of $I(n)$ is:

$$\rho(n)=\frac{1}{2}\sum_{m=1}^{Q}A_m^2\cos 2\pi f_m n\ . \tag{5}$$

From (5), the total power of interference signal is:

$$I_0=\rho(0)=\frac{1}{2}\sum_{m=1}^{Q}A_m^2\ . \tag{6}$$

2.2. Autoregressive Interference

The other type of interference is modeled as an autoregressive process. We say that the time series $u(n)$, $u(n-1)$, ..., $u(n-M)$ represents the realization of an autoregressive process (AR) of order M if it satisfies the difference equation:

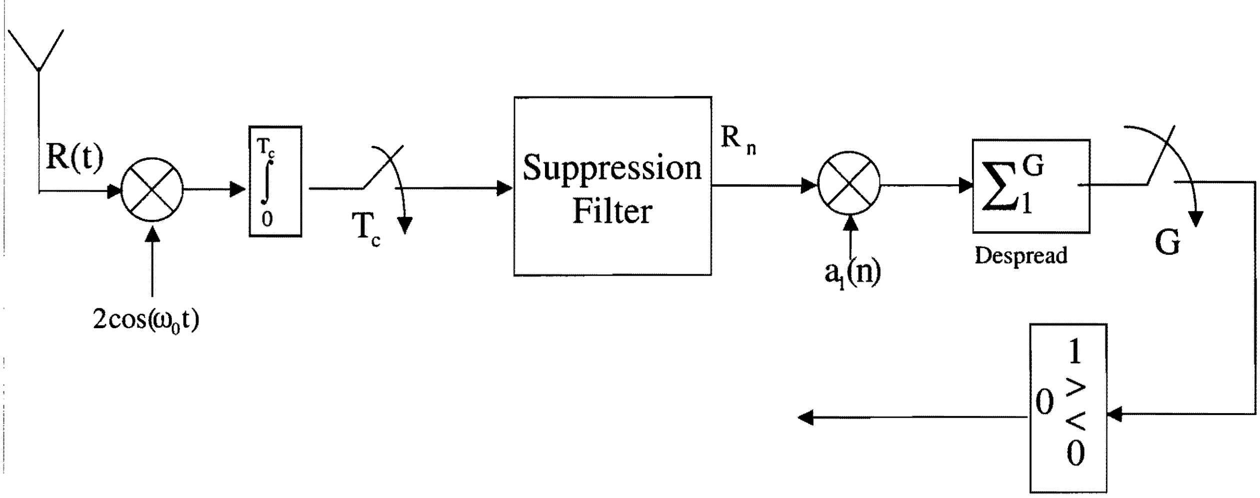

Figure 2. Receiver model of CDMA overlay system.

$$u(n)+a_1u(n-1)+a_Mu(n-M)=\nu(n)\,, \tag{7}$$

where $a_1, a_2, \ldots, a_M$ are constants called the AR parameters, and $\{\nu(n)\}$ is a white-noise process. The term $a_k u(n-k)$ is an inner product of a_k and $u(n-k)$, where $k = 1,\ldots\ldots, M$. The left side of (7) represents the convolution of the input sequence $\{u(n)\}$ and the sequence of parameters $\{a_n\}$. The transfer function $H(z)$ of the AR model is completely defined by specifying the locations of its poles, as shown by [13].

$$H(z)=\frac{\sigma_\upsilon}{\left(1-p_1z^{-1}\right)\left(1-p_2z^{-1}\right)\ldots\ldots\left(1-p_Mz^{-1}\right)}\,. \tag{8}$$

The parameters $p_1, p_2, \ldots, p_M$ are the poles of $H(z)$; they are defined by the roots of the characteristic equation:

$$1+a_1z^{-1}+a_2z^{-2}+\ldots\ldots+a_Mz^{-M}=0\,. \tag{9}$$

For an AR process of order two, the power can be adjusted using [13]:

$$J_0=\left(\frac{1+a_2}{1-a_2}\right)\frac{\sigma_\nu^2}{\left[(1-a_2)^2-a_1^2\right]} \tag{10}$$

where σ_ν^2 is the variance of zero-mean white noise $\{\nu(n)\}$.

3. NARROWBAND INTERFERENCE SUPPRESSION FILTER

One of the most powerful NBI rejection techniques is the method of linear predictive analysis. The importance of this method lies both in its ability to provide accurate estimates of NBI parameters, and in its relative speed of computation. In the literature [4–7], the theory of linear prediction and how it can be used in the design of a filter that tends to suppress the NBI while leaving the SS signal relatively unchanged, is well documented.

Filters used for the above purpose can be fixed or adaptive. The design of fixed filters is based on prior knowledge of both the signal and interference. Adaptive filters, on the other hand, have the ability to adjust their own parameters automatically and their design requires little or no prior knowledge of signal or interference characteristics. Implementation of linear prediction method using LMS and LMK adaptive algorithms is presented in this section.

3.1. Least Mean Square (LMS) Algorithm

The structure of LMS adaptive algorithm is shown in the block-diagram of Figure 3. Basically, it consists of a combination of two basic processes:

1. An adaptive process, which involves the automatic adjustment of a set of tap weights.
2. A filtering process, which involves (*a*) forming the inner product of a set of tap inputs and the corresponding set of tap weights emerging from the adaptive process to produce an estimate of a desired response, and (*b*) generating an estimation error by comparing this estimate with the actual of the desired response. The estimation error is in turn used to actuate the adaptive process, thereby closing the feedback.

During the filtering process, $x(n)$ is supplied along with usual tap inputs at time n. The idea is to fit a filter operating on the reference signal $x(n)$ to generate $\hat{x}(n)$ which is considered an estimate of the NBI. The design involves on-line estimation of the filter parameters by minimizing the mean square error defined as:

$$\begin{aligned} \mathrm{e}(n) &= x(n)-\hat{x}(n) \\ &= x(n)-\sum_{i=1}^{M} w_i x(n-i)\,. \end{aligned} \tag{11}$$

Let $\mathbf{w}(n)$ denote the value of the tap-weight vector at time n. The expanded form of the tap-weight vector is described by:

$$\mathbf{w}^{\mathrm{T}}(n)=[w_1(n), w_2(n), \ldots\ldots\ldots, w_M(n)]\,. \tag{12}$$

Also, let $\mathbf{X}_n$ denote the tap-input vector at time n. That is,

$$\mathbf{X}_n^{\mathbf{T}} = [x(n-l),........,x(n-M)]. \tag{13}$$

Therefore, we can write:

$$\begin{aligned}\varepsilon(n) &= E[|e(n)|^2] \\ &= E[\mathrm{x}(n) - \mathbf{w}^{\mathbf{T}}(n)\mathbf{X}_n]^2.\end{aligned} \tag{14}$$

Here, we use the method of *steepest descent* for finding the minimum point of $\varepsilon(n)$. This method is an iterative procedure that has been used to find extrema of nonlinear functions. According to the method of steepest descent, the update value of the tap-weight vector at time $n+1$ is computed by using the simple recursive relation.

$$\begin{aligned}\mathbf{w}(n+1) &= \mathbf{w}(n) + \frac{1}{2}\mu[-\nabla\varepsilon(n)] \\ &= \mathbf{w}(n) + \frac{1}{2}\mu\left[\frac{\partial\varepsilon(n)}{\partial\mathbf{w}(n)}\right] \\ &= \mathbf{w}(n) + \mu E\left[e(n)\mathbf{X}_n\right].\end{aligned} \tag{15}$$

A practical limitation with this algorithm is that the expectation $E[e(n)\mathbf{X}_n]$ is generally unknown. Therefore, it must be replaced with an estimate. One possible choice is to approximate $\varepsilon(n)$ by its instantaneous value $e^2(n)$. Then, at each iteration of the adaptive process, we have a gradient estimate of the form:

$$\begin{aligned}\nabla\varepsilon(n) &= \frac{\partial e^2(n)}{\partial\mathbf{w}(n)} \\ &= 2e(n)\mathbf{X}_n.\end{aligned} \tag{16}$$

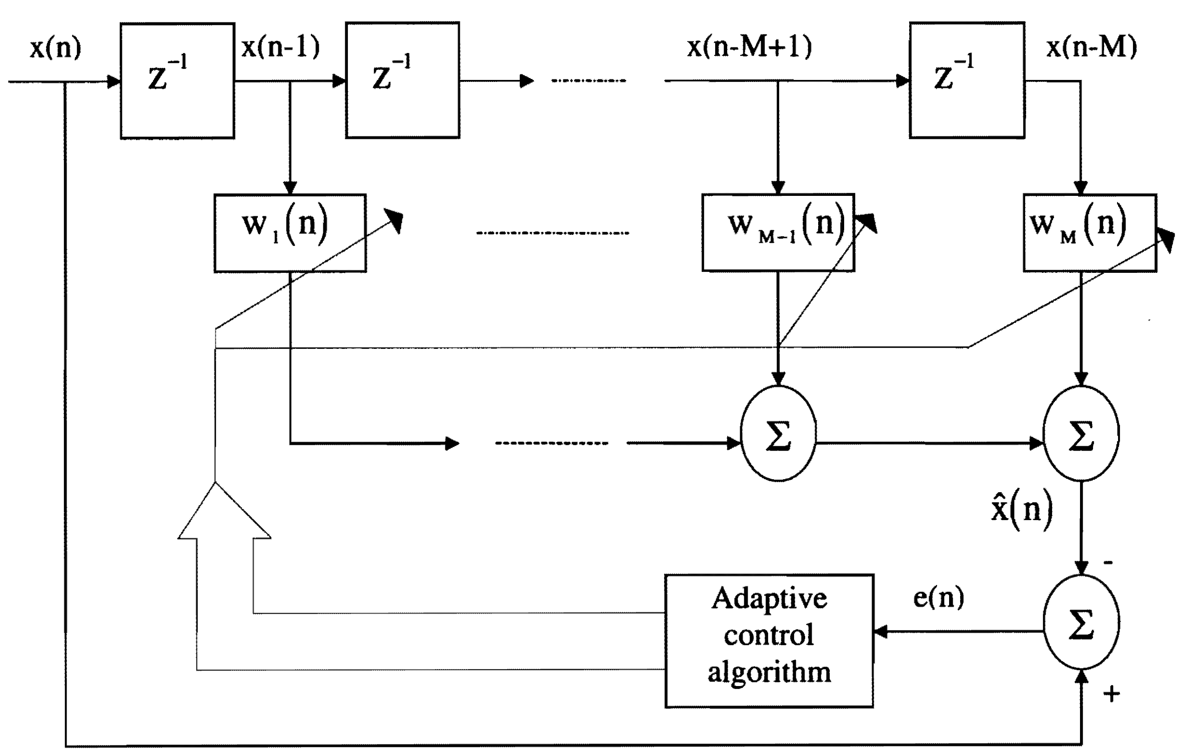

Figure 3. Structure of adaptive transversal filter.

With this simple estimate of the gradient, we can now specify a steepest descent type of the adaptive algorithm. From (22) and (23), we have:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)\mathbf{X}_n . \tag{17}$$

This is the *Least Mean Square* (LMS) algorithm. In this algorithm, the choice of step size μ is critical. The parameter μ controls the stability and rate of convergence of the algorithm. If it is too small, then the convergence can be unacceptably slow. On the other hand, if μ is just below the upper limit which is given later in (18), this means that the algorithm converges quickly with the presence of fluctuations in the adaptive filter coefficients during steady state operation. The choice of μ involves a trade-off between speed of convergence and the desire to keep the variance of coefficients small. To guarantee convergence in the mean-square sense, it is shown in [13] that the step size parameter μ must satisfy the following condition

$$0 < \mu < \mu_{\max} , \tag{18}$$

where

$$\mu_{\max} = \frac{2}{\text{total input power}} . \tag{19}$$

Here, the total input power refers to the sum of the mean square values of the individual inputs: $x(n-1)$, $x(n-2)$,...., $x(n-M)$. Therefore,

$$\mu_{\max} = \frac{2}{M c_2(0)} . \tag{20}$$

3.2. Least Mean Kurtosis (LMK) Algorithm

There is considerable amount of research activity dedicated to adaptive algorithms that use non mean-square cost functions. Important applications are in blind equalization [13] and system identification [17]. In blind equalization, cost functions with higher order moments of the equalizer output are used in order to correctly identify the phase characteristics of the channel. Many significant contributions exist but we would like to mention the work by Shalvi and Weinstein [18, 19] which uses the same Higher Order Statistical measure; the kurtosis, that the LMK algorithm is based upon.

Unlike the LMS algorithm which minimizes the mean square value ε, the LMK algorithm minimizes the negated kurtosis of the error signal:

$$J(n) \underline{\underline{\Delta}} 3E^2\{e^2(n)\} - E\{e^4(n)\} . \tag{21}$$

The LMK algorithm is a steepest descent procedure. The gradient vector corresponding to (21) is [20]:

$$\nabla J(n) = \frac{\partial J(n)}{\partial \mathbf{w}(n)} = -4E[(3E\{e^2(n)\}e(n) - e^3(n))\mathbf{X}_n] . \tag{22}$$

For algorithm construction, $E\{e^2(n)\}$ in (22) must be replaced with an approximation that can be computed in real-time. For this purpose, we define the alternative gradient vector:

$$\nabla J(n) = -4E\left[\left(3\sigma_e^2(n)e(n) - e^3(n)\right)\mathbf{X}_n\right] , \tag{23}$$

where the variance of the prediction error; $\sigma_e^2(n)$ satisfies the relation,

$$\sigma_e^2(n) = \beta\sigma_e^2(n-1) + (1-\beta)e^2(n) \qquad 0 < \beta < 1, \tag{24}$$

and β is the *forgetting factor* that controls the memory of the error power estimator. Therefore, the gradient descent based update equation of the LMK algorithm is:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 4E(3\sigma_e^2(n) - e^2(n))\mathrm{e}(n)\mathbf{X}_n \tag{25}$$

where μ is the adaptation gain. This algorithm requires four extra multiplications and two extra additions compared to the LMS.

It is worthnoting that the LMK algorithm, as defined in (25), is very responsive to large values of $e(n)$. It may quickly become unstable unless a very small adaptation gain parameter is employed. Unfortunately, no convergence analysis has been yet reported in the literature for the LMK algorithm when it is operated in the linear prediction mode. However, we provide next, a modification to the LMK algorithm which aims to circumventing the algorithm stability problem.

Let:

$$\alpha(n) = 4\mu(3\sigma_e^2(n) - e^2(n)) . \tag{26}$$

Therefore, the update equation of the LMK algorithm can be written in the following compact form:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \alpha(n)e(n)\mathbf{X}_n . \tag{27}$$

Comparing (17) and (27), we notice that the LMK algorithm is simply a variable step size LMS algorithm where the step size adjustment is controlled by the square of prediction error and its variance. Intuitively speaking, a large prediction error will cause the step size to increase to provide faster tracing while a small prediction will result in a decrease in the step size to yield smaller misadjustment. It is, however, important to note the increased responsiveness of the LMK algorithm to large errors impacts on the stability of adaptation.

In what follows, we provide a modification to the LMK algorithm. This modification is based on replacing the variable step size $\alpha(n)$ by a clipped version of it to ensure that the mean-square error of the algorithm remains bounded. The algorithm modified step size $\hat{\alpha}(n)$ is given by:

$$\hat{\alpha}(n) = \begin{cases} \alpha(n) & \textit{if } \alpha(n) < \rho\mu_{\max} \\ \rho\mu_{\max} & \textit{if } \alpha(n) \geq \rho\mu_{\max} , \end{cases} \tag{28}$$

where $0 < \rho < 1$ and $\mu_{\max}$ is the upper bound of the LMS adaptation gain parameter. Therefore, using (28), the stability of the LMK algorithm is guaranteed provided that $\mu_{\max}$ is properly selected. The step size $\hat{\alpha}(n)$ is now controlled by the parameter ρ and $\mu_{\max}$. The constant $\mu_{\max}$ is determined using the simple relation (20).

4. SYSTEM PERFORMANCE

In digital communications there are usually two important parameters that reveal the system performance; namely the bit error rate (BER) and signal to noise ratio improvement (SNRI). Based on these two parameters, the system performance can be evaluated with and without the presence of the suppression filter. This section addresses these two measures of performance. In addition, the rate of convergence of the LMS and LMK suppression algorithms is discussed.

4.1 Signal to Noise Ratio Improvement

In order to examine the performance of interference suppression filters, we assume the received signal $\{R_n\}$ to be consisted of a spread data signal $\{S_n\}$, interference signal $\{I_n\}$, and Gaussian noise $\{N_n\}$. The SNR improvement factor is the ratio of the SNR at the filter output over the SNR at the filter input. The improvement in the SNR performance due to the use of suppression filter in the CDMA receiver can be calculated as follows:

$$\text{SNR at the filter input} = \frac{E\left[\|S_n\|^2\right]}{E\left[\|R_n - S_n\|^2\right]} \tag{29}$$

$$\text{SNR at the filter output} = \frac{E\left[\|S_n\|^2\right]}{E\left[\|\varepsilon_n - S_n\|^2\right]} \tag{30}$$

where, $\varepsilon_n = R_n - \hat{R}_n$

$\hat{R}_n$: is the predicted estimate signal, and therefore:

$$\text{SNR Improvement} = \frac{E\left[\|R_n - S_n\|^2\right]}{E\left[\|\varepsilon_n - S_n\|^2\right]} . \tag{31}$$

This expression is normally used for the evaluation of the suppression filter and in this paper as a measure of system performance.

4.2 Bit Error Rate (BER)

Except for a few cases, it is generally difficult to arrive at an exact closed form expression for the bit error probability of a communication system, even under the assumption of white Gaussian noise interference. When the interference is not modeled as white noise, the analysis is even more difficult. For coherent BPSK, the bit error probability against white Gaussian noise and over slowly fading channel is given by [16]:

$$P_e = \frac{1}{2}\left[1 - \sqrt{\frac{r_b}{1+r_b}}\right] \approx \frac{1}{4r_b} . \tag{32}$$

where r_b denotes the average signal to noise ratio. The above expression also applies to BPSK/SS communication system operating over slowly fading channel with the presence of white Gaussian noise.

For CDMA situation, the performance limitation is due to the interference from other similar spread spectrum signals. However, if the number of chips per bit is large, according to the central limit theorem, the output of a coherent detector can be shown [21, 22] to be nearly Gaussian. Therefore, the classical expression for BER of an uncoded coherent BPSK demodulator is additive when white Gaussian noise is applied. When the communication channel is subjected to fading upper and lower bounds on the average probability of error obtained [23, 24] for such a situation. When a narrowband interference is applied into the BPSK/SS system and therefore a suppression filter is added into coherent detector the situation is even more difficult to analyze. Approximate expressions have been developed by a limited number of authors [7]. For CDMA system with the presence of narrowband interference, no general expression exists for BER or even its upper bound. However, when the number of active users is large, it is shown in [25] that, according to the central limit theorem, the sum of internal interference generated by the suppression filter, the narrowband interference terms and the multiple access interference terms can be approximated by Gaussian random variables. Therefore, the resulting bit error rate can then be evaluated by the expression in (32), where:

$$1/r_b = \left[\frac{E_b}{N_0}\right]^{-1} \sum_m w_m^2 + \left[\frac{J}{GS}\right] * \sum_{m1,m2} w_{m1} w_{m2} \sigma_j^2(m_1, m_2)$$
$$+ \frac{(K-1)}{G}\left[\frac{2}{3}\sum_m w_m^2 + \frac{1}{3}\sum_m w_m w_{m+1}\right] \tag{33}$$

where:

- S : The average CDMA signal power
- E_b : The average energy per bit of CDMA user = ST_b
- N_0 : The power density of additive white Gaussian noise
- G : The processing gain
- σ_j^2 : The interfering narrowband correlation function.

The above result was obtained for narrowband interference modeled as BPSK digital signal. In our case, however, the interference signal is also narrowband but modeled as either a multitone interference or AR signal. The difference between the models will not affect the general result which was based on the central limit theorem and general expression given in (32), as long as r_b still denotes the average signal to noise ratio, with "noise" taken to be the sum of the contributions due to the narrowband interference, the multiple access interference, and thermal noise. The same approach has been followed in [26], where PSK interference signal has been modeled by a second ARMA process.

4.3. System Mismatch (SM)

Through the adaptive process the coefficients of the adaptive filter go to the optimum values, with certain rate of convergence. This rate of convergence can be defined as the number of iterations required for the algorithm, in response to stationary inputs, to converge "close enough" to the optimum Wiener solution in the mean-square sense. A fast rate of convergence allows the algorithm to adapt rapidly to a stationary environment of unknown statistics.

In our simulation the rate of convergence is described using the expression below which is often called in the literature [15] as the system mismatch (SM).

$$SM = 10\log_{10}\frac{\left\|\mathbf{w}-\mathbf{w}_{opt}\right\|^2}{\left\|\mathbf{w}_{opt}\right\|^2}, \tag{34}$$

where

$\mathbf{w}$: Adaptive filter coefficients

$\mathbf{w}_{\text{opt}}$: Optimum Wiener solution.

In this section, some simulation examples together with some numerical results are presented to demonstrate the performance of an LMK algorithm based adaptive suppression filter in CDMA network. This filter performance is compared against the LMS algorithm. The CDMA system performance is evaluated in the presence of both types of interference signals models: multitone interference and autoregressive interference.

5. SIMULATION AND RESULTS

The simulated CDMA system handles 10 users, the Interference power to Signal power Ratio (ISR), J/S=20dB, and has a processing gain of 127 with pseudorandomly generated spreading sequence using Gold codes. All the results generated by simulation are obtained by averaging over 50 Monte Carlo runs. The performance measures used are SNR Improvement, BER and the speed of convergence. The fixed step size of both the LMS and modified-LMK algorithms has been given identical values.

5.1. Multiple Tones Interference

In order to evaluate the adaptive LMK filter performance under the circumstances of multiple tones interference, we obtained the SNRI, BER, and system mismatch for the processing gain $G=127$ and filter coefficients $M=5$, 10, and 20. The interference signal has 20dB power equally distributed on the multiple frequencies. The results are shown in Figures 4–6 for the five tones interference. Figure 4 shows that the SNRI trend of the two algorithms with E_b/N_o is the same, except for a slight difference between the SNRI of the two algorithms for almost all values of E_b/N_o. This result is applicable for the tap weights $M=5$, 10, and 20.

The BER results (Figure 5) show the same behavior except a shift difference between the LMS and LMK results. The improvement in speed of convergence of the LMK compared to the LMS algorithms is clearly demonstrated in Figure 6. For example, the LMS needed 5000 more iterations compared to the LMK to reach its steady state, when the number of coefficients is $M=20$.

The above situation has been repeated for the case of ten tones and number of filter coefficients $M=20$. The results are shown in Figure 7. The same conclusions stated above can be easily shown from these results. The improvement of the LMK speed of convergence has even been clearly demonstrated, where 8000 iterations is now the difference between the LMK and LMS speed under the conditions of the previous example.

To see the effect of the number of active users of the CDMA system on the LMS and LMK filters. The approximate BER results against the number of users have been plotted in Figure 8, for different values of J/S. These curves show that the number of users has the same effect on both the LMK and LMS, under the same parameters of J/S, and the number of tones.

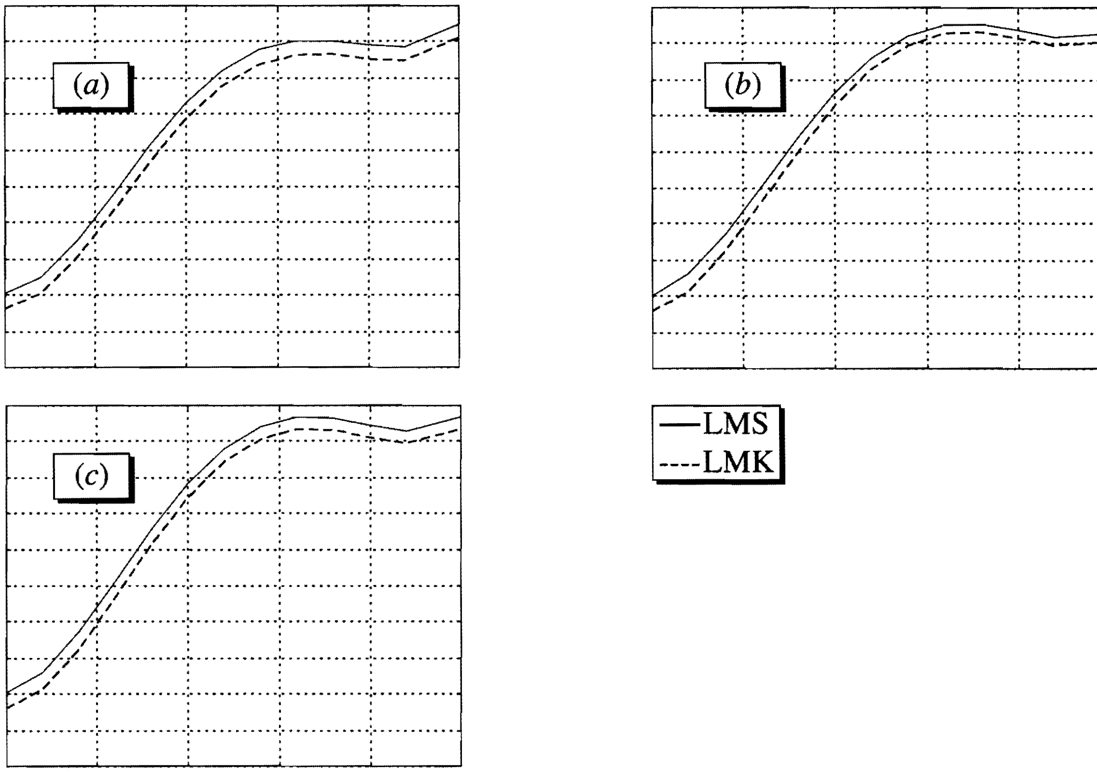

Figure 4. The SNRI against the signal-to-noise ratio E_b/N_o *with five tones, gain* G=*127, and filter coefficients:* (a) M=*5:* (b) M=*10:* (c) M=*20.*

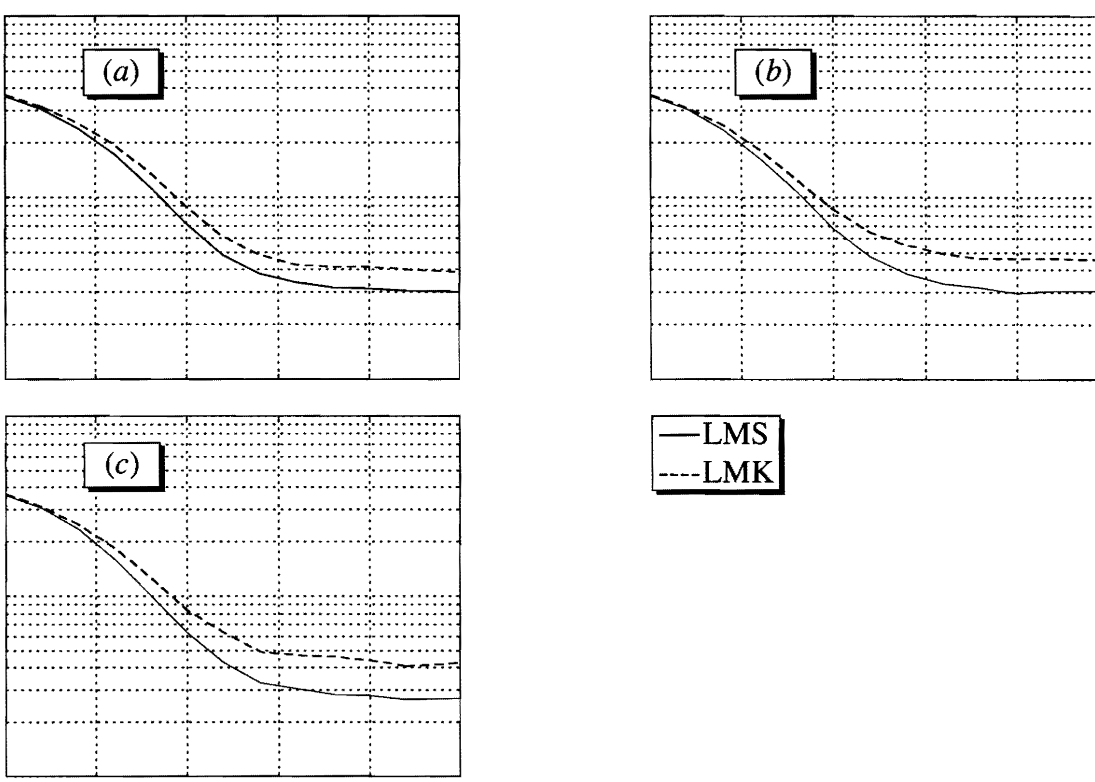

Figure 5. The BER against the signal-to-noise ratio E_b/N_o *with five tones, gain* G=*127, and filter coefficients:* (a) M=*5;* (b) M=*10;* (c) M=*20.*

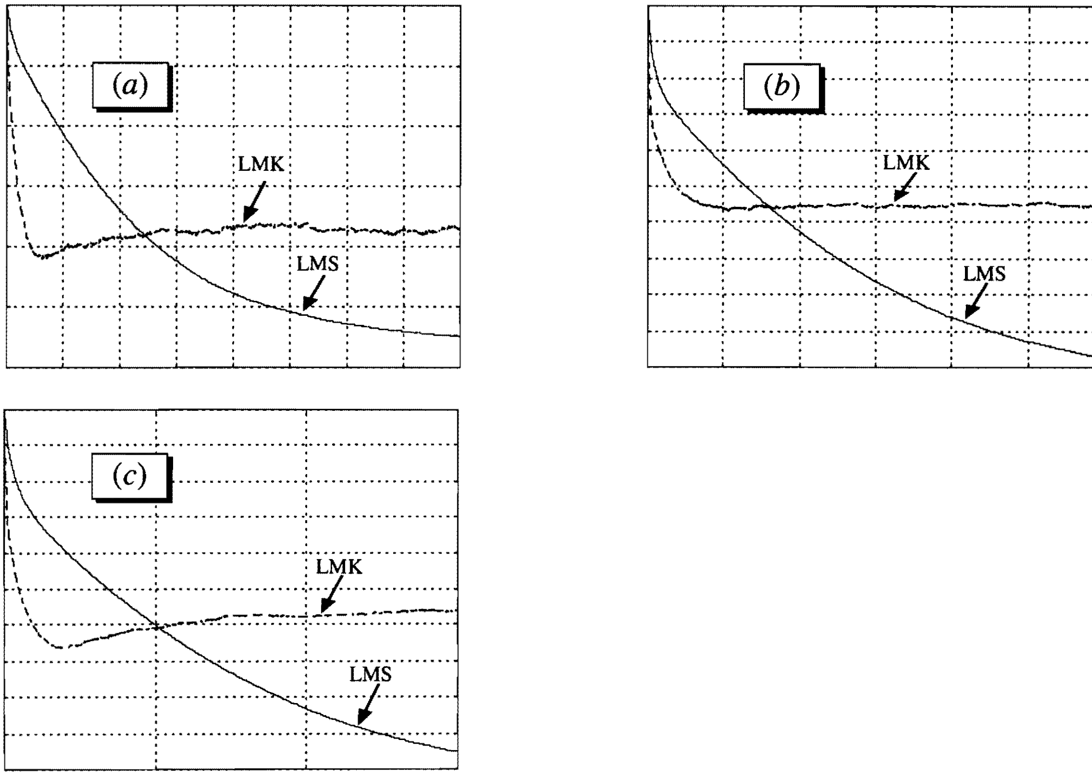

Figure 6. The SM against the number of iterations with five tones, gain G=*127, and filter coefficients:* (a) M=*5; (*b) M=*10; (*c) M=*20.*

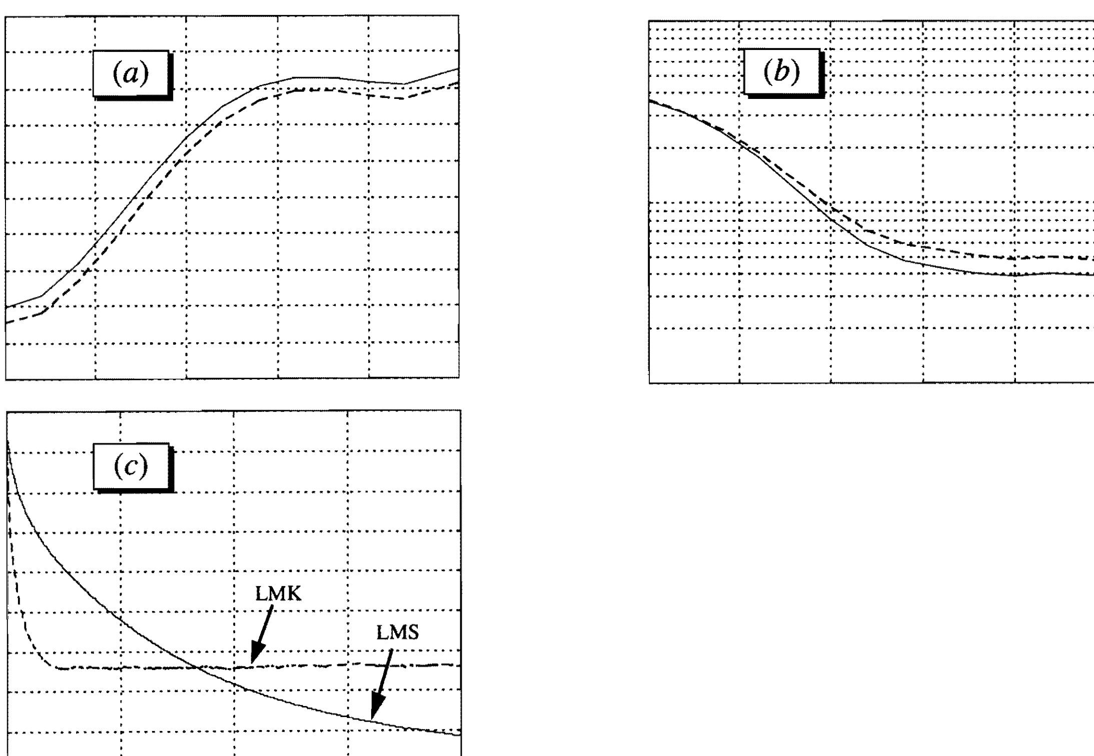

Figure 7. System performance with ten tones, gain G=*127, and filter coefficients* M=*20: (*a) *SNRI; (*b) *BER; (*c) *SM.*

5.2. Autoregressive Interference

To examine the effect of the interference bandwidth on the LMK and LMS filter, the autoregressive format is used to model the interference signal as discussed in Section 2.2. The bandwidth variation of the interference is represented by the double pole locations (*e.g.*, 0.9 and 0.8) corresponding to $a_1 = -1.8$, $a_2 = 0.81$, and $a_1 = -1.6$, $a_2 = 0.64$, respectively.

The SNRI, BER, and system mismatch results are shown in Figures 9 and 10. The same conclusion adopted for the multiple tone interference is applied again here: meaning that the LMK has a better speed of convergence performance over the LMS, especially when the interference has a wider bandwidth. For example, the LMK is faster than LMS by 20000 iterations when the poles location is at 0.8, the number of coefficients is 10, and processing gain is 127.

To see the effect of the number of active users of the CDMA system on the LMS and LMK filters when the bandwidth of interference is varied. The approximate BER results against the number of users have been plotted in Figure 11, for different values of *J/S*. The curves show that the number of users has the same effect on both the LMK and LMS, under the same parameters of *J/S*, and the change of bandwidth of interference.

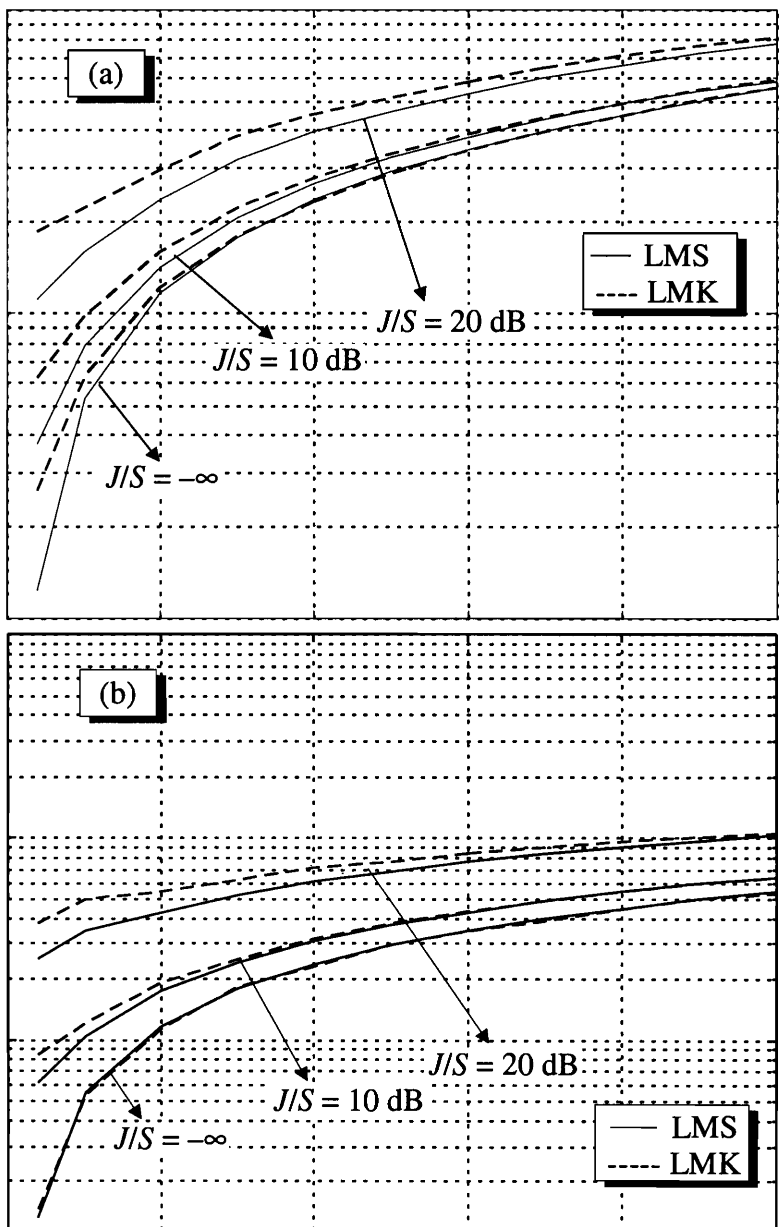

Figure 8. The BER against the number of active user, with gain G=*127, and coefficients* M=*6:* (a) *five tones;* (b) *ten tones.*

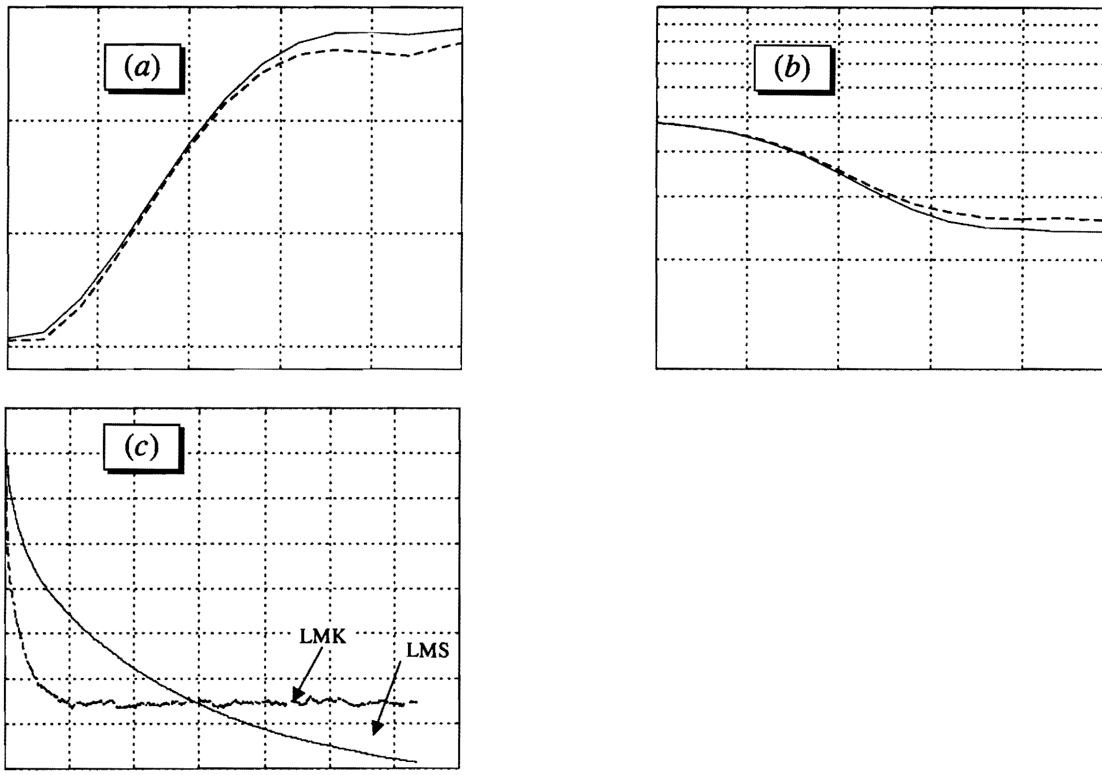

Figure 9. System performance against AR interference with poles at (0.9), gain G=*127, and filter coefficients* M=*10:* (a) *SNRI;* (b) *BER;* (c) *SM.*

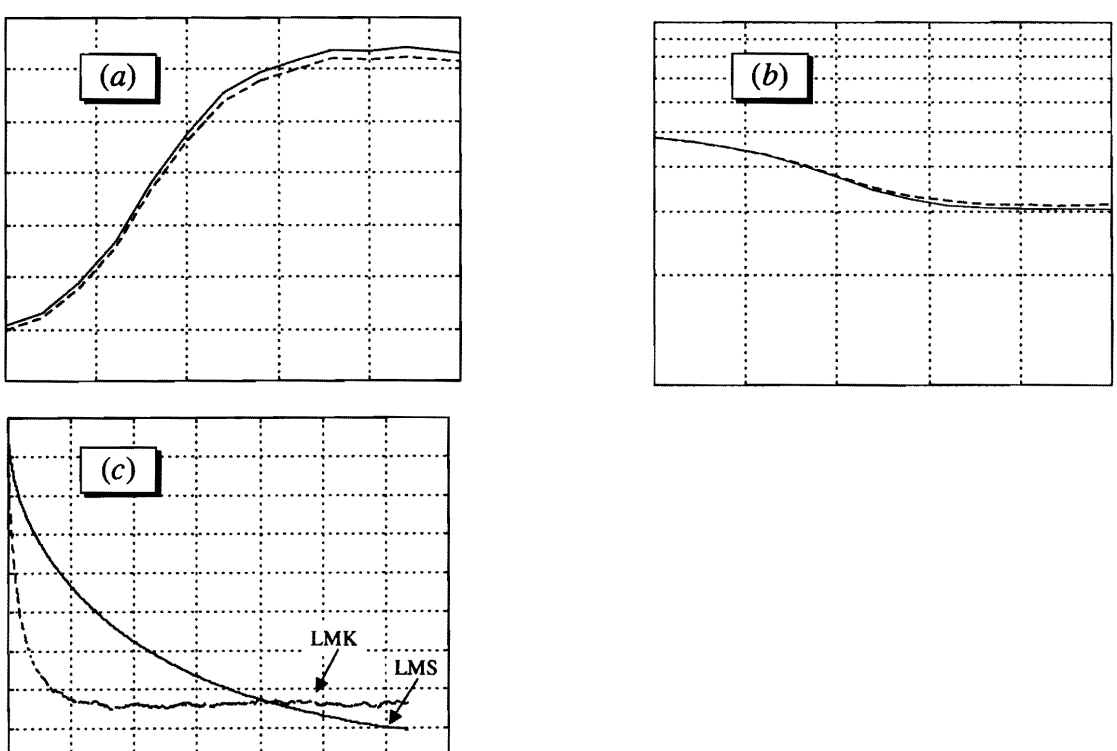

Figure 10. System performance against AR interference with poles at (0.8), gain G=*127, and filter coefficients* M-*10:* (a) *SNRI;* (b) *BER;* (c) *SM.*

6. CONCLUSIONS

In this paper, we have considered a new adaptive method for NBI cancellation in DSSS systems. The method presented is based on linear prediction analysis and the least mean kurtosis algorithm. In particular, an investigation of an LMK algorithm based transversal filter is addressed in the context of NBI suppression in a CDMA system operating in a cellular radio environment. This investigation is based on computer simulation results of the SNRI, BER, and SM. These performance measures have been calculated for two models of interference, namely: multitone and autoregressive interferences, with a wide range of values for the system parameters. These parameters included processing gain, filter length, number of active users of the CDMA system, interference power-to-signal ratio (J/S), number of tones, and interference bandwidth. Moreover, these new results of LMK filter are compared with those using second order statistics, *i.e.*, LMS filter.

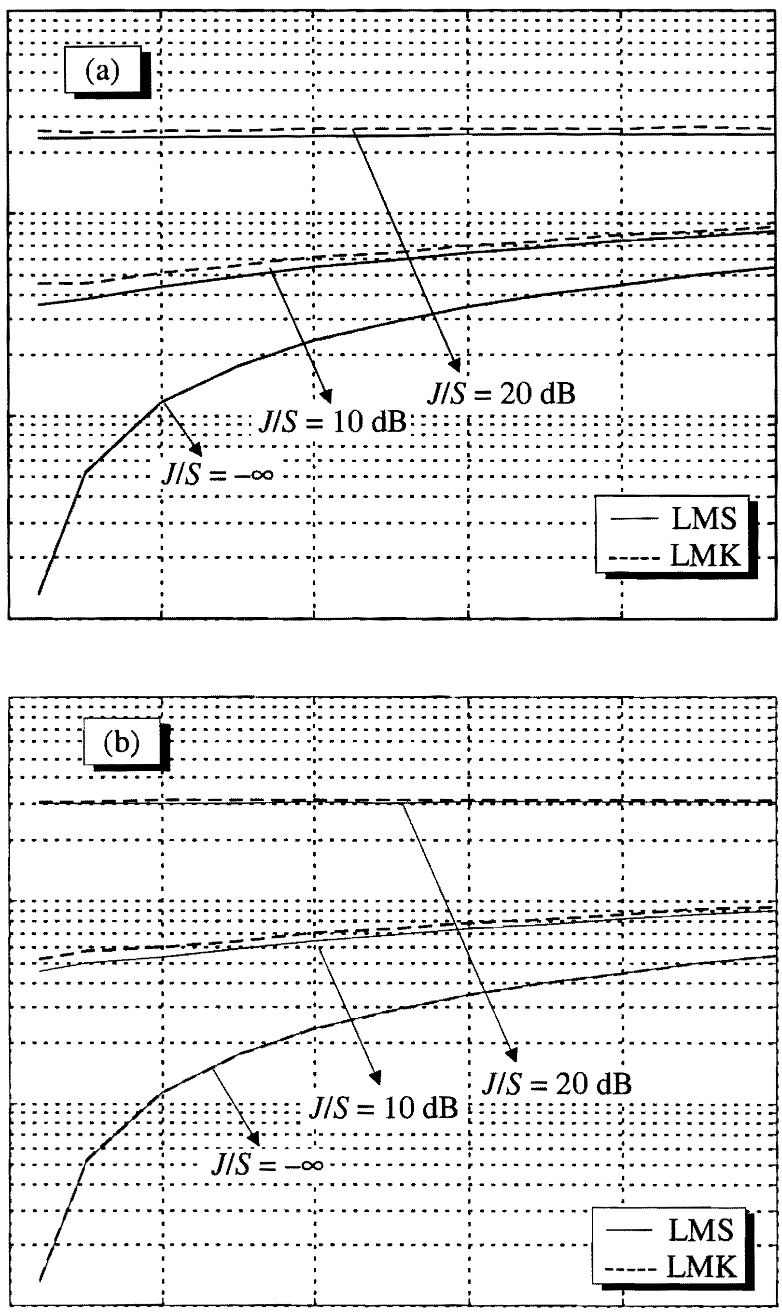

Figure 11. The BER against the number of users, gain G=127, number of coefficient is (M=6), and poles at: (a) 0.9 and (b) 0.8.

Simulation results have demonstrated that the LMK algorithm is capable of providing performance comparable to that of the LMS algorithm. However, an advantage of the LMK algorithm over the LMS algorithm is that the LMK algorithm converges faster than the LMS algorithm. This improvement in performance of the LMK algorithm compared to the LMS algorithm is achieved only at a larger number of tones or a wider bandwidth of the interference. The two algorithms, however, show close by similar performance in terms of the SNRI and BER. This fact has been demonstrated by numerous simulation tests. These results also are verified when the number of active users is changed. It has been shown, in this paper, that the LMK algorithm can simply be viewed as variable step size least-mean square algorithm where the step size adjustment is controlled by the square of prediction error and its variance. A modification to the LMK algorithm is provided such that its mean-square error remains bounded. The LMK algorithm is not difficult to implement. It requires four extra multiplications and two extra additions compared to the LMS algorithm.

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