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CDMA 시스템에서 단계별 가중치를 갖는 병렬 간섭 제거 기법

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Stage-by-stage Weighted Parallel Interference Cancellation for CDMA Systems

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요 약

부분 병렬 간섭 제거 기법[1]은 기존의 병렬 간섭 제거 기법에 비해 그 성능이 훨씬 우수하다. 부분 병렬 간섭 제거 기법에서, 현 단계의 판정기 입력 데이터는 수신신호, 다원 접속 간섭의 추정치와 전 단계의 판정기 입력 데이터를 이용하여 얻어진다. 본 논문에서는, 수신 신호와 다원 간섭 신호의 추정치 만을 이용하여 현 단계의 판정기 입력 데이터를 구하는 새로운 부분 병렬 간섭 제거 기법을 유도하고, 이동통신 환경에서 실제적인 시스템 구조를 제안하며 시뮬레이션을 통하여 그 성능을 분석한다.

ABSTRACT

The partial parallel interference cancellation proposed in [1] demonstrates substantial performance improvement compared to the conventional parallel interference cancellation. The derivation of the partial parallel interference cancellation is based on the observation of the received signal, the estimate of multiple access interference, and the input data to decision device obtained at the previous iteration. In this paper, we derive a new partial parallel interference cancellation, in which the input data to decision device at the present stage is determined only by the received signal and the estimate of the multiple access interference. In addition, a practical structure for mobile communication environments is proposed and its performance is also evaluated based on computer simulation results.

I. Introduction

Direct-sequence code-division multiple access (DS-CDMA) technology is the most attractive and promising candidate for the next generation wireless communication systems such as IMT-2000 and UMTS. The performance and/or the capacity of conventional CDMA detectors are greatly influenced by the multiple access interference (MAI) contributed by the other users. Even though optimal multi-user detection is not interference-limited, it is too complex to be implemented. Thus, a compromise between performance and system complexity gives a birth to sub-optimal multi-user detection like the interference cancellation (IC) including successive IC (SIC) [2]-[5] and parallel IC (PIC) [6]-[16]. The PIC detector estimates and subtracts out all of the MAI in parallel for all users. The multistage iterative approach that we assume here is proposed in [7]-[12], in which at each stage of the iteration it is attempted for each user to completely cancel the MAI caused by all the other users. We refer this multistage PIC to as the conventional PIC

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(CPIC). To achieve the acceptable performance improvement with the CPIC, in which the total amount of the MAI estimate is cancelled at each stage of iteration, the accurate channel estimation and bit decision are required. However, they are not guaranteed in low signal to noise and interference ratio (SNIR) situations. To overcome the drawback of the CPIC, a few modified CPIC schemes were proposed based on similar idea. One is the adaptive hybrid serial/parallel IC (AHSPIC) [17], which is devised for the (multipath) fading environments. The basic idea of the AHSPIC is that it keeps the detectors with low SNIR input signals from participating in cancellation. That is, the detectors not involved in earlier cancellations are to be included in later cancellations when sufficient SINR is guaranteed after canceling the signals with high power in earlier cancellations. The partial parallel interference cancellation [1] (which is referred to as the PPIC here) is another approach designed with focusing on the case of fixed channels with equal power. In the PPIC the partial amount of MAI estimate is cancelled at each stage of iteration. As the IC operation progresses (i.e., as the fidelity of the MAI estimate goes up), the weight determining the amount of the MAI estimate to be cancelled increases. The input data to decision device of the PPIC at the present stage is obtained as a weighted sum of the received signal from which the MAI estimate at the present stage is cancelled out and the input data to decision device at the previous stage. In this paper, we present that the input data to decision device at the previous stage contains all the previous stages' MAI estimates, which are less reliable than the MAI estimate at the present stage. And we devise a new PPIC, in which the input data to decision device at the present stage is determined only by observing the received signal and the MAI estimate at the present stage. In addition, we propose a practical implementation of the new derivation and evaluate the performance in an asynchronous Rayleigh fading channel. The system model dealt with is described in section II. In section III, we introduce the PPIC and point out its drawback. A new derivation of PPIC is made in section VI and its practical implementation is proposed in section V. Results of the computer simulation of our practical system are presented in section VI, and in section VII, we give our conclusions drawn from our results.

II. System Model

Consider a pilot symbol aided coherent BPSK transmitter, then the received complex baseband signal of M users is given by

$$r(t) = \sum_{j=1}^{M} \sum_{m=-\infty}^{\infty} \alpha_j(t)\, e^{i\phi_j(t)} a_j(m) \, c_j(t-mT_b-\tau_j(t)) + n(t), \tag{1}$$

where $a_j(m)$ is the m-th transmitted data symbol with bit length T_b, $\alpha_j(t)$, $\phi_j(t)$ and $\tau_j(t)$ are channel amplitude, phase and time delay for the j-th user, respectively, and $n(t)$ is an additive white Gaussian noise (AWGN) with zero-mean and power spectral density of $N_0/2$. With chip length T_c, $N=T_b/T_c$ is the processing gain. The j-th user's spreading waveform is given by $c_j(t) = \sum_{n=1}^{N} c_{j,n} h(t-nT_c)$, where $c_{j,n}$ is the j-th user's spreading sequence and $h(t)$ is a normalized chip pulse shaping filter. Throughout this paper, the i-th user's signal is taken to be the desired one.

Assuming that the receiver has knowledge of the time delay of the desired signal, we set $\tau_i(t) \equiv 0$ without loss of generality. For a given set of user codes, the normalized cross correlation is defined as

$$\gamma_{ij} = \begin{cases} \frac{1}{T_b}\int_0^{T_b} c_i(t)\, c_j(t-\tau_j(t))\, dt, & i \neq j \\ 1, & i=j \end{cases}$$
$$\text{for } i,j=1,2,\cdots,M. \tag{2}$$

The normalized projection of the received signal on user i's code is

$$\begin{aligned} y_i &= \frac{1}{T_b}\int_0^{T_b} r(t)\, c_i(t)\, dt, \quad i=1,2,\cdots,M \\ &= \frac{1}{T_b}\int_0^{T_b} \{ \sum_{j=1}^{M} \alpha_j(t)\, e^{i\phi_j(t)} a_j c_j(t-\tau_j(t)) + n(t)\}\, c_i(t)\, dt. \end{aligned} \tag{3}$$

Assuming a slowly varying fading channel, the component of the normalized received signal vector corresponding to the i-th user when multiplied by $e^{-j\phi_i}$, is obtained as

$$e^{-j\phi_i} y_i = \frac{1}{T_b}\left[\int_0^{T_b} \alpha_i a_i c_i^2(t)\,dt + \sum_{j\neq i}^{M} \int_0^{T_b} \alpha_j a_j e^{j(\phi_j-\phi_i)} c_j(t-\tau_j(t))\, c_i(t)\,dt + \int_0^{T_b} e^{-j\phi_i} n(t)\, c_i(t)\,dt\right] \quad (4)$$
$$= \alpha_i a_i + \sum_{j\neq i}^{M} \alpha_j a_j e^{j(\phi_j-\phi_i)} \gamma_{ij} + e^{-j\phi_i} n_i,$$

for $i = 1, 2, \ldots, M$, where n_i is a zero-mean complex Gaussian random variable (r.v.). Let $Y_i = e^{-j\phi_i} y_i$, then the input signal of IC detector is written as

$$Y_i = \alpha_i a_i + I_i + N_i\,, \quad (5)$$

where $I_i = \sum_{j\neq i}^{M} \alpha_j a_j e^{j(\phi_j-\phi_i)} \gamma_{ij}$ denotes the MAI by the i-th user due to the remaining M-1 users and $N_i = e^{-j\phi_i} n_i$ is a zero-mean complex Gaussian r.v. with variance two (unit variance per component.)

III. Partial PIC

The CPIC scheme significantly enhances the performance and/or capacity of CDMA detectors by estimating and canceling the total amount of interference at each stage. However, the CPIC seems not the best approach since the total interference is canceled at every stage, even when the decisions are quite unreliable at the early stages. In order to improve the performance, it is desirable not to cancel the total interference in the early stages but to increase the weight of interference being cancelled as IC operation progresses [1].

From (5) we have an expression of the form

$$Y_i = \alpha_i a_i + \hat{I}_i + W_i \;:\; W_i = I_i - \hat{I}_i + N_i, \quad (6)$$

where $\hat{I}_i$ denotes an estimate of I_i based on estimates of the other users' data bits. In an iterative structure, (6) can be written as

$$Y_i = \alpha_i a_i + \hat{I}_i(k) + W_{i1}(k) \quad (7)$$

where $\hat{I}_i(k) = \sum_{j\neq i}^{M} \alpha_j \hat{a}_j(k-1)\, e^{j(\phi_j-\phi_i)} \gamma_{ij}$ is the MAI estimate at the k-th stage and $W_{i1}(k) = I_i - \hat{I}_i(k) + N_i$ can be modeled as a zero-mean Gaussian r.v. with variance $\sigma_{i1}^2(k)$ since the residual interference $I_i - \hat{I}_i(k)$ is assumed as a zero-mean Gaussian r.v. In order to include the information on the desired user's bit, $\tilde{a}_i(k-1)$, available at the previous stage for the current bit estimate, it is possible to assume

$$\tilde{a}_i(k-1) = \alpha_i a_i + W_{i2}(k-1) \quad (8)$$

where $W_{i2}(k-1)$ is a Gaussian r.v. of zero mean and variance $\sigma_{i2}^2(k-1)$. Assume that $W_{i1}(k)$ and $W_{i2}(k)$ are correlated with coefficient $\rho_i(k)$.

In [1], by jointly observing Y_i and $\tilde{a}_i(k-1)$ given a_i and $\hat{I}_i(k)$, a nonlinear MMSE estimator at the k-th stage is obtained as

$$\begin{aligned}\hat{a}_i(k) &= \tanh\big(\beta_i(k)\,[p(k)\,\mathrm{Re}[\,Y_i - \hat{I}_i(k)] \\ &\quad + (1-p(k))\,\tilde{a}_i(k-1)]\big)\end{aligned} \quad (9)$$

where $\beta_i(k) = \dfrac{\alpha_i[\sigma_{i1}^2(k) + \sigma_{i2}^2(k-1) - 2\rho_i(k)\sigma_{i1}(k)\sigma_{i2}(k-1)]}{\sigma_{i1}^2(k)\,\sigma_{i2}^2(k-1)\,(1-\rho_i^2(k))}$.

The input data to decision device at the k-th stage, $\tilde{a}_i(k)$, can be defined by

$$\tilde{a}_i(k) \equiv p(k)\,\mathrm{Re}[\,Y_i - \hat{I}_i(k)] + (1-p(k))\,\tilde{a}_i(k-1), \quad (10)$$

with $\tilde{a}_i(0) = \mathrm{Re}[\,Y_i\,]$, where $p(k)\,(0 \le p(k) \le 1)$ is a weight factor that represents the amount of cancellation at the k-th stage. As previously mentioned, it is referred to as the partial PIC (PPIC). In [1], it is asserted that the performance improvement of the PPIC is achieved by including the information on the bit estimate, namely, the tentative decision $\hat{a}_i(k-1)$, or, betters yet, the input data to decision device $\tilde{a}_i(k-1)$, which are available at the previous stage. We show, however, that the performance improvement is not due to the use of $\tilde{a}_i(k-1)$. The recursive formula (10) can be rewritten as the following explicit form :

$$\tilde{a}_i(k) = \mathrm{Re}\Big[Y_i - p(k)\,\hat{I}_i(k) - \sum_{n=1}^{k-1} \bar{p}(n)\,\hat{I}_i(n)\Big] \quad (11)$$

with $\tilde{a}_i(0) = \mathrm{Re}[Y_i]$, where $\bar{p}(n) = p(n) \prod_{l=n+1}^{k} (1-p(l))$ is a weight factor determining the amount of $\hat{I}_i(n)$ being cancelled, for $n=1, \cdots, k-1$. As shown in (11), $\tilde{a}_i(k-1)$ generates the MAI estimate components from $\hat{I}_i(0)$ up to $\hat{I}_i(k-1)$. Consequently, the inclusion of $\tilde{a}_i(k-1)$ in (10) causes the inclusion of all the poor MAI estimates of previous stages, which may degrade the performance and makes the IC system more complicated. On the other hand, since $p(k) \gg \bar{p}(n)$, for $n=1, \cdots, k-1$, it is certain that the performance improvement of the PPIC comes from the term $Y_i - p(k)\,\hat{I}_i(k)$.

IV. The Proposed PPIC

From (5), let the output of the i-th user's correlator be

$$Y_i = \alpha_i a_i + W_i \quad (12)$$

where $W_i = I_i + N_i$. Since the MAI I_i and the MAI estimate $\hat{I}_i(k)$ are the sum of several users' signals and of their estimates, respectively, they can be assumed to have the Gaussian distribution by the central limit theorem. So we assume that W_i has a PDF of $N(0, \sigma_{i1}^2)$ and the MAI estimate $\hat{I}_i(k)$ has a PDF of $N(0, \sigma_{i2}^2(k))$. Let $\rho_i(k)$ be the correlation coefficient of W_i and $\hat{I}_i(k)$.

In this section, we pursue to find a nonlinear minimum mean square error (MMSE) estimator for a_i given Y_i and $\hat{I}_i(k)$ defined by

$$\hat{a}_i(k) \equiv E[a_i \mid Y_i,\ \hat{I}_i(k)]. \quad (13)$$

Based on the assumption in (12), the r.v. Y_i given a_i has a PDF of $N(\alpha_i a_i,\ \sigma_{i1}^2)$, By jointly observing Y_i and $\hat{I}_i(k)$ given a_i, the conditional PDF $p(Y_i, \hat{I}_i(k) \mid a_i)$ is derived as follows:

$$\begin{aligned}
p(Y_i, \hat{I}_i(k) \mid a_i) &= \frac{1}{(2\pi)^2 \sigma_{i1}\sigma_{i2}(k)\sqrt{1-\rho_i^2(k)}} \\
&\quad \exp\Big\{-\frac{1}{2(1-\rho_i^2(k))} \\
&\quad \Big[\frac{(Y_i-\alpha_i a_i)^*(Y_i-\alpha_i a_i)}{\sigma_{i1}^2} + \frac{\hat{I}_i^*(k)\,\hat{I}_i(k)}{\sigma_{i2}^2(k)} \\
&\quad - \frac{\rho_i(k)\big((Y_i-\alpha_i a_i)^*\hat{I}_i(k) + (Y_i-\alpha_i a_i)\hat{I}_i^*(k)\big)}{\sigma_{i1}\sigma_{i2}(k)}\Big]\Big\} \\
&= \frac{1}{(2\pi)^2 \sigma_{i1}\sigma_{i2}(k)\sqrt{1-\rho_i^2(k)}} \\
&\quad \exp\Big\{-\frac{1}{2\sigma_{i1}^2\sigma_{i2}^2(k)(1-\rho_i^2(k))}\,[\sigma_{i2}^2(k)[Y_i^* Y_i + \alpha_i] \\
&\quad + \sigma_{i1}^2 \hat{I}_i^*(k)\,\hat{I}_i(k) - \rho_i(k)\,\sigma_{i1}\sigma_{i2}(k) \\
&\quad [Y_i^*\hat{I}_i(k) + \hat{I}_i^*(k)\,Y_i] - \alpha_i a_i(\sigma_{i2}^2(k)[Y_i^* + Y_i] \\
&\quad - \rho_i(k)\,\sigma_{i1}\sigma_{i2}(k)[\hat{I}_i^*(k) + \hat{I}_i(k)])]\Big\} \\
&= C\exp\Big\{\alpha_i a_i\Big[\frac{\sigma_{i2}^2(k)\,\mathrm{Re}[Y_i] - \rho_i(k)\,\sigma_{i1}\sigma_{i2}(k)\,\mathrm{Re}[\hat{I}_i(k)]}{\sigma_{i1}^2\sigma_{i2}^2(k)(1-\rho_i^2(k))}\Big]\Big\} \\
&= C\exp\Big\{a_i \frac{\alpha_i}{\sigma_{i1}^2(1-\rho_i^2(k))}\,\mathrm{Re}\Big[Y_i - \frac{\rho_i(k)\,\sigma_{i1}}{\sigma_{i2}(k)}\,\hat{I}_i(k)\Big]\Big\}, \quad (14)
\end{aligned}$$

where the operator $(\cdot)^*$ denotes the complex conjugate, the constant C represents the terms not containing a_i, and $\mathrm{Re}[z] = (z+z^*)/2$ for complex number z is used. By letting $\beta_i(k) = \alpha_i/\sigma_{i1}^2(1-\rho_i^2(k))$, $p_i(k) = \rho_i(k)\,\sigma_{i1}/\sigma_{i2}(k)$ and $\lambda_i(k) = \mathrm{Re}[Y_i - p_i(k)\,\hat{I}_i(k)]$ in (14), the conditional joint PDF has a simple expression as

$$p(Y_i, \hat{I}_i(k) \mid a_i) = C\exp(a_i\beta_i(k)\,\lambda_i(k)). \quad (15)$$

Now the *a posteriori* probability $p(a_i \mid Y_i, \hat{I}_i(k))$ can be written as

$$\begin{aligned}
p(a_i \mid Y_i, \hat{I}_i(k)) &= \frac{p(Y_i, \hat{I}_i(k) \mid a_i)\,p(a_i)}{p(Y_i, \hat{I}_i(k))} \\
&= \frac{p(Y_i, \hat{I}_i(k) \mid a_i)\,p(a_i)}{p(Y_i, \hat{I}_i(k) \mid a_i = 1) + p(Y_i, \hat{I}_i(k) \mid a_i = -1)},
\end{aligned} \quad (16)$$

where the Bayes' rule and the equiprobable properties of the data streams are used in the last equality. Using (15), (16), the nonlinear estimate $\hat{a}_i(k) = E[a_i \mid Y_i,\ \hat{I}_i(k)]$ for a_i is obtained by

$$\begin{aligned} E[a_i \mid Y_i,\ \hat{I}_i(k)] &= 1 \cdot p(a_i = 1 \mid Y_i,\ \hat{I}_i(k)) \\ &\quad + (-1) \cdot p(a_i = -1 \mid Y_i,\ \hat{I}_i(k)) \\ &= \frac{p(Y_i,\ \hat{I}_i(k) \mid a_i = 1) P(a_i = 1) - p(Y_i,\ \hat{I}_i(k) \mid a_i = -1) P(a_i = -1)}{p(Y_i,\ \hat{I}_i(k) \mid a_i = 1) P(a_i = 1) + p(Y_i,\ \hat{I}_i(k) \mid a_i = -1) P(a_i = -1)} \\ &= \frac{C \exp(\beta_i(k)\lambda_i(k)) - C \exp(-\beta_i(k)\lambda_i(k))}{C \exp(\beta_i(k)\lambda_i(k)) + C \exp(-\beta_i(k)\lambda_i(k))} \\ &= \tanh(\beta_i(k)\lambda_i(k)). \end{aligned} \tag{17}$$

By letting the input data to decision device be $\tilde{a}_i(k) = \lambda_i(k)$, the nonlinear MMSE estimate (or the tentative decision) $\hat{a}_i(k) = \tanh(\beta_i(k)\tilde{a}_i(k))$ has the same form as in [1], where, however, $\beta_i(k)$ and $\tilde{a}_i(k)$ are different from those obtained in [1]. (See (9) and (10) above.) The input data to decision device of the proposed scheme is given by

$$\tilde{a}_i(k) = \mathrm{Re}[Y_i - p_i(k)\hat{I}_i(k)]. \tag{18}$$

Note that $\tilde{a}_i(k)$ does not include the term $\tilde{a}_i(k-1)$, differently from (10). The weight factor $p_i(k)$ can be rewritten as

$$p_i(k) = \frac{Cov(W_i,\ \hat{I}_i(k))}{Var(\hat{I}_i(k))} = \frac{Cov(Y_i,\ \hat{I}_i(k))}{Var(\hat{I}_i(k))}. \tag{19}$$

For successive stages, $Var(\hat{I}_i(k))$ decreases and $Cov(Y_i,\ \hat{I}_i(k))$ increases since the MAI estimates becomes more reliable. Consequently, the weight factor $p_i(k)$ increases as the stage progresses toward the final bit decision. This means that as the tentative decisions become more reliable the *amount* of MAI estimate being cancelled increases. Another factor is $\beta_i(k)$ which indicates the fidelity of the input data to decision device. As IC operation progresses, $\beta_i(k)$ also increases since $\rho_i(k)$ approaches to 1 as k increases. In the case of the fixed channels with equal power as in [1], the factors $\beta_i(k)$ and $p_i(k)$ depend only on stage k, but not on i. Even in the time-varying channels with a large number of users as in [17], those factors do not nearly depend on i. Thus, the proposed weighted PIC scheme is referred to as the *stage-by-stage weighted PIC* (SWPIC) and from now on we remove the user index i. The weight factors in the PPIC are also determined stage by stage. Note that the SWPIC is equivalent to the CPIC when $p(k) = 1$, for all k. (Also, the CPIC can be derived as the similar way to the SWPIC (see Appendix).)

V. Practical Structure

Fig. 1 depicts a practical structure of the multi-stage SWPIC derived in the previous chapter. Each IC stage consists of three functional blocks: detection, regeneration and subtraction. The estimates for regenerating MAI, such as tentative decision and estimates of channel information, are inherently achieved in conventional coherent detectors; the amplitude and phase are estimated from a sample-mean of pilot symbols and the channel delay is obtained from timing circuitry such as tracking and acquisition.

For a cost-effective system, a linear finite-bit quantizer is employed as the tentative decision device. The transfer function of the linear finite-bit quantizer is quite similar to that of the nonlinear hyperbolic tangent quantizer, as shown in Fig. 2. The new subtraction block first generates the interference-subtracted resultant by subtracting weighted estimates of all users from the received signal and then adds the weighted estimate of desired user's signal to the interference-subtracted resultant. The subtraction block outputs the received signal whose weighted MAI estimate contributed to desired user is cancelled out. Since interference-subtracted resultant is commonly used for all users, the proposed subtraction scheme reduces the number of adders and connections for subtraction approximately to $1/M$ of that required for the PPIC (M is the number of detectors in service). Based on the main idea of the proposed subtraction scheme, the multi-stage SWPIC can be implemented with the one-stage structure proposed in [3]. If the input signal to finite impulse response (FIR) filter is binary, the filter with low complexity can be implemented; thus, the data of one is fed into the pulse shaping filter and the tentative decision value is multiplied behind the filter (see Fig. 1.)

VI. Computer Simulation Results

Based on the computer simulations, the performance of the IC detectors is evaluated up to three stages. The bandwidth is 3.968 MHz and the carrier frequency is 2.0 GHz. It is assumed that the transmitted signal undergoes an asynchronous Rayleigh fading channel, reflecting a reverse link in the CDMA systems. A pilot symbol is inserted into the symbol stream at every 4 information symbols. The mobile speed is 50km/h, the spreading factor is 16, and the additive noise component is ignored.

Fig. 3 shows the effect of $p(k)$ on bit error rate (BER) performances of the proposed SWPIC with a

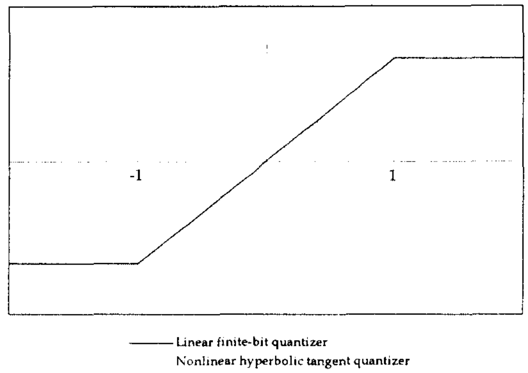
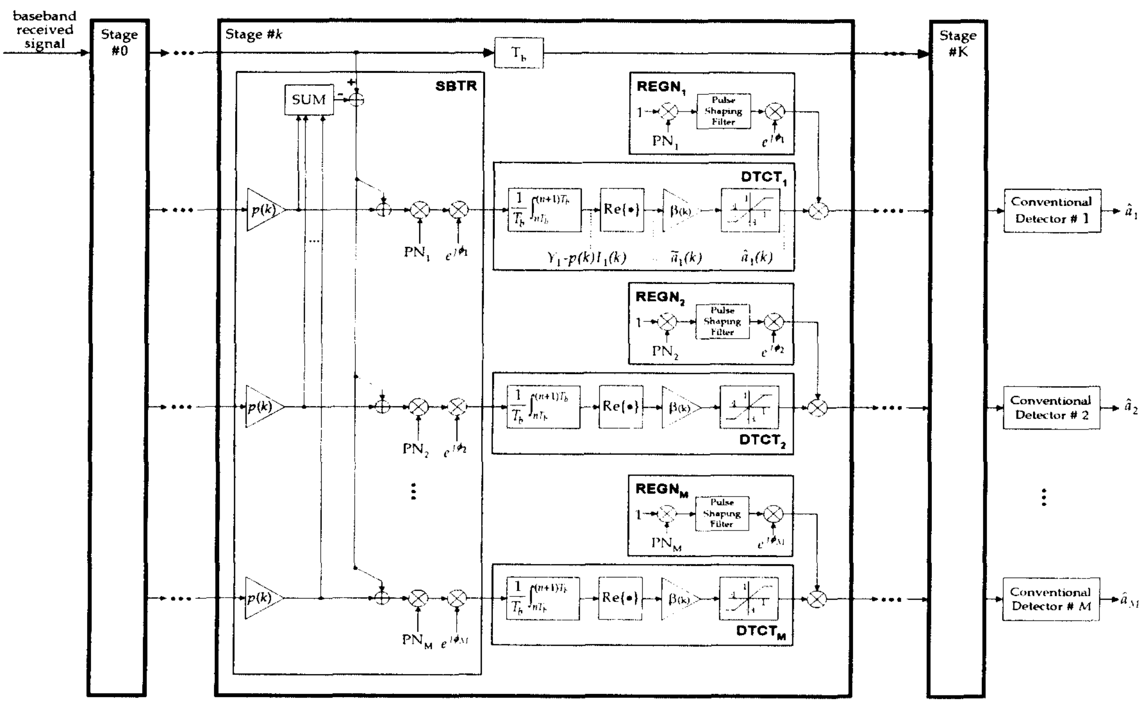


Fig. 2 Transfer functions of linear finite bit quantizer and nonlinear hyperbolic tangent quantizer.

hard limited decision device ($\beta(k)=\infty$). The values of $p(1)=0.5$, $p(2)=0.7$ and $p(3)=1.9$ are the same as those given in [1], and the values $p(1)=0.6$, $p(2)=0.8$ and $p(3)=1.0$ are chosen arbitrarily.



DTCT : Detector
REGN : Regenerator
SBTR : Subtractor

Fig. 1 The multistage implementation of the proposed IC (SWPIC) system.

The SWPIC with $p(1) = 1$, $p(2) = 1$ and $p(3) = 1$ is equivalent to the CPIC. From Fig. 3, we can see that remarkable improvement in performance of the SWPIC has obtained over the CPIC. As expected, the CPIC has good performance when the number of users is small. However, as the number of users increases, performance of the CPIC severely degrades and the performance improvement of the SWPIC relative to the CPIC increases. Also, it is observed that the optimum choice of $p(k)$ depends on the number of users. Fig. 4 demonstrates the effect of $\beta(k)$ on BER performance of the SWPIC, where the weight factors of MAI estimate are fixed as $p(1) = 0.6$, $p(2) = 0.8$, $p(3) = 1.0$. We can see that the slope of hyperbolic tangent function, $\beta(k)$, is another factor to be optimized at each iteration stage. When $\beta(k) = 1$, (i.e., when the tentative decisions are made only with $\hat{a}_i(k)$), performance of the SWPIC is inferior. Using a hard limit device $(\beta(k) = \infty)$ for making the tentative decisions at the stages of IC process seems to be appropriate, when the number of users is small (< 15). The SWPIC with properly chosen $\beta(k)$ is superior to that with $\beta(k) = \infty$.

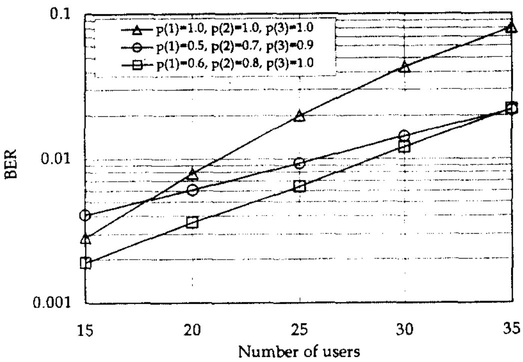


Fig. 3 BER performance of the SWPIC as a function of $p(k)$ (with a hard limited decision device $(\beta(k) = \infty)$).

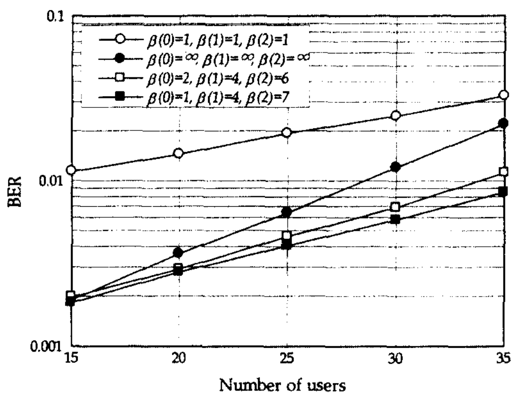


Fig. 4 BER performance of the SWPIC as a function of $\beta(k)$ ($p(1) = 0.6$, $p(2) = 0.8$, $p(3) = 1.0$).

VII. Conclusion

We make a new derivation of partial interference cancellation, which does not include the input data to decision device obtained at the previous stage, and propose a practical structure of the IC system based on the derivation. Compared with PPIC in [1], the proposed one has simple structure by reducing the number of adders and connections as well as excluding the use of the input data to decision device obtained at the previous stage. It can also save cost by using the linear finite-bit quantizer as the tentative decision device. In addition, its performance is evaluated in an asynchronous Rayleigh fading channel. With optimal weight factors, it is expected that the proposed IC system may be slightly superior to the PPIC system.

In both PPIC and SWPIC, the weight factors of interference estimates are artificially determined stage by stage. In practical mobile communication environments such as multi-path fading channels, the fidelity of interference estimate of each user (or path) is unequal[1] and time varying. Thus, as a further study, it is desirable to device IC systems, which adjust weight factors of interference estimate user by user (or path by path) and adaptively to the changing environments.

References

1. D. Divsalar, M. K. Simon, and D. Raphaeli, "Improved parallel interference cancellation for CDMA,"

1) The fidelity of the interference estimate for a user (or a path) with high power is obviously higher than that with low power.

IEEE Trans. Commun., vol. 46. No. 2, pp. 258-268, Feb. 1998.
2. A. J. Viterbi, "Very Low Rate Convolutional Codes for Maximum Theoretical Performance of Spread-Spectrum Multiple-Access Channels," IEEE JSAC, vol. 8. No. 4, pp. 641-649, May 1990.
3. R. Kohno et al., "Combination of an Adaptive Array Antenna and a Canceller of Interference for Direct-Sequence Spread-Spectrum Multiple-Access System," IEEE JSAC, vol. 8. No. 4, pp. 675-682, May 1990.
4. A. Duel-Hallen, J. Holtzman, and Z. Zvonar, "Multi-User Detection for CDMA Systems," IEEE Pers. Commun., vol. 2, No. 2, pp. 46-58, Apr. 1995.
5. I. Seskar, "Practical Implementation of Successive Interference Cancellation," presentation, WINLAB Semi-Annaul Res. Rev., Rutgers Univ., NJ, Apr. 26, 1996.
6. R. Kohno et al., "An Adaptive Canceller of Co-channel Interference for Spread-Spectrum Multiple-Access Communication Networks in a Power Line," IEEE JSAC, vol. 8. No. 4, pp. 691-699, May 1990.
7. M. K. Varanasi and B. Aazhang, "Multistage detection in asynchronous code-division multiple-access communications," IEEE Trans. Commun., vol. 38, pp. 509-519, Apr. 1990.
8. M. K. Varanasi and B. Aazhang, "Near-Optimum Detection in Synchronous Code-Division Multiple-Access Systems," IEEE Trans. Commun., vol. 39, No. 5, pp. 725-736, May 1991.
9. Y. C. Yoon, R. Kohno, and H. Imai, "Cascaded Co-channel Interference Canceling and Diversity Combining for Spread-Spectrum Multi-access over Multipath Fading Channels," in SITA '92, Minakami, Japan, Sept. 8-11, 1992.
10. Y. C. Yoon, R. Kohno, and H. Imai, "A Spread-Spectrum Multi-access System with a Cascade of Co-channel Interference Cancellers for Multipath Fading Channels," in ISSSTA '92, Yokihama, Japan, Nov. 29 - Dec. 2, 1992.
11. Y. C. Yoon, R. Kohno, and H. Imai, "A Spread-Spectrum Multiaccess System with Co-channel Interference Cancellation," IEEE J. Select. Areas Commun., vol. 11, pp. 1076-1075, Sept. 1993.
12. M. Kawabe, T. Kato, A. Kawahashi. T. Sato, and A. Fukasawa, "Advanced CDMA Scheme Based on Interference Cancellation," Proc. VTC '93, pp. 448-451, May 18-20, 1993.
13. P. Patel and J. Holtzman, "Performance Comparison of a DS/CDMA system Using a Successive Interference Cancellation (IC) Scheme and Parallel IC Scheme under Fading," Proc. ICC '94, New Orleans, LA, pp. 510-514, May 1994.
14. S. Moshavi, Multistage Linear Detectors for DS-CDMA Communications, Ph.D. dissertation. Dept. Elec. Eng., City Univ. NY, Jan. 1996.
15. S. Moshavi, "Multi-User Detection for DS-CDMA Communications," IEEE Commun. Mag., pp. 124-136, Oct. 1996.
16. R. M. Buehrer and B. D. Woerner, "Analysis of Adaptive Multistage Interference Cancellation for CDMA Using an Improved Gaussian Approximation," Proc. IEEE MILCOM '95, San Diego, CA, pp. 1195-1199, Dec. 1994.
17. S. R. Kim, J. G. Lee, and H. Lee, "Interference cancellation scheme with simple structure and better performance," Electron. Lett., vol. 32, no. 23, pp. 2115-2117, Nov. 7, 1996.

Appendix
Derivation of the Conventional PIC

Under the Gaussian assumption of the MAI I_i and the MAI estimate $\hat{I}_i(k)$, let the interference of the i-th user be given by

$$I_i = \hat{I}_i(k) + \varepsilon_i(k) \tag{A1}$$

where $\varepsilon_i(k)$ is the estimation error of I_i at the k-th stage and is assumed as a zero-mean Gaussian r.v. Then, from (5),

$$Y_i = \alpha_i a_i + \hat{I}_i(k) + \varepsilon_i(k) + N_i \equiv \alpha_i a_i + \hat{I}_i(k) + W_i(k), \tag{A2}$$

where $W_i(k)$ is assumed to be a zero-mean complex

Gaussian r.v. with variance $\sigma_i^2(k)$, say. The input signal Y_i given by a_i and $\hat{I}_i(k)$, is also a complex Gaussian r.v. with mean $\alpha_i a_i + \hat{I}_i(k)$ and variance $\sigma_i^2(k)$ and the PDF

$$
\begin{aligned}
p(Y_i | a_i, \hat{I}_i(k)) &= \frac{1}{2\pi\sigma_i(k)} \\
&\exp\left[-\frac{1}{2\sigma_i^2(k)} (Y_i - \alpha_i a_i - \hat{I}_i(k))^* (Y_i - \alpha_i a_i - \hat{I}_i(k)) \right] \\
&= \frac{1}{2\pi\sigma_i(k)} \exp\left\{ -\frac{1}{2\sigma_i^2(k)} [(Y_i - \hat{I}_i(k))^* (Y_i - \hat{I}_i(k)) \right. \\
&\left. + \alpha_i^2 a_i^2 - \alpha_i a_i [(Y_i - \hat{I}_i(k))^* + (Y_i - \hat{I}_i(k))]] \right\} \\
&= C \exp\left[a_i \frac{d_i}{\sigma_i^2(k)} Re[Y_i - \hat{I}_x(k)] \right],
\end{aligned} \tag{A3}
$$

where the constant C includes terms not depending on a_i. It can be written in the desired form

$$
p(Y_i | a_i, \hat{I}_i(k)) = C \exp[a_i \beta_i(k) \lambda_i(k)], \tag{A4}
$$

where $\beta_i(k) = \frac{\alpha_i}{\sigma_i^2(k)}$ and $\lambda_i(k) = \mathrm{Re}[Y_i - \hat{I}_i(k)]$.

To obtain an MMSE estimator of bit a_i, the *a posteriori* probability is

$$
\begin{aligned}
&p(a_i | Y_i, \hat{I}_i(k)) \\
&= \frac{p(Y_i | \hat{I}_i(k), a_i) p(\hat{I}_i(k), a_i)}{p(Y_i | \hat{I}_i(k), a_i = 1) P\{\hat{I}_i(k), a_i = 1\} + p(Y_i | \hat{I}_i(k), a_i = -1) P\{\hat{I}_i(k), a_i = -1\}}.
\end{aligned} \tag{A5}
$$

The nonlinear MMSE estimate $E[a_i | Y_i, \hat{I}_i(k)]$ of a_i is given by

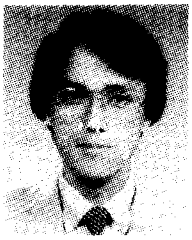
$$
\begin{aligned}
E[a_i | Y_i, \hat{I}_i(k)] &= p(a_i = 1 | Y_i, \hat{I}_i(k)) \\
&\quad - p(a_i = -1 | Y_i, \hat{I}_i(k)) \\
&= \frac{p(Y_i | \hat{I}_i(k), a_i = 1) - p(Y_i | \hat{I}_i(k), a_i = -1)}{p(Y_i | \hat{I}_i(k), a_i = 1) + p(Y_i | \hat{I}_i(k), a_i = -1)} \\
&= \tanh(\beta_i(k) \lambda_i(k)).
\end{aligned} \tag{A6}
$$

Since the input data to decision device at k-th stage is given by

$$
\tilde{a}_i(k) \equiv \lambda_i(k) = \mathrm{Re}[Y_i - \hat{I}_i(k)], \tag{A7}
$$

the nonlinear MMSE can be obtained as

$$
\hat{a}_i(k) \equiv E[a_i | Y_i, \hat{I}_i(k)] = \tanh(\beta_i(k) \tilde{a}_i(k)).
$$



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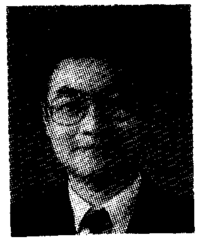

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