An Asynchronous Schwarz-IC Cascade MUD Detection Algorithm for Multiple Access Mobile Communication System

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Abstract. The multi-user detection precision and interference suppression processing efficiency of single successive interference cancellation (SIC), parallel interference cancellation (PIC) algorithm and the cascade structure interference cancellation (IC) algorithm are always affected by single-stage and multi-stage detection error diffusion. This paper focuses on the detection error diffusion of multiple access communication system with strong multiple access interference (MAI) and inter symbol interference (ISI). In this paper, a Schwarz-IC (S-IC) cascade multi-user detection (MUD) algorithm based on the monotone convergence characteristics of the Schwarz algorithm, is proposed for the multiple access mobile asynchronous communication system. The Schwarz-IC algorithm can precisely control the sub-domain boundary value of the user load power in system, efficiently track the change wireless channel, avoid the single-stage or multi-stage detection error diffusion of single interference cancellation algorithm and improve the detection convergence. Simulation results show that the Schwarz-IC algorithm is of better BER performance, detection accuracy and dynamic tracking capability.

Keywords: Multiple access interference · Successive interference cancellation · Parallel interference cancellation · Schwarz

1 Introduction

In the modern wireless mobile communication, public land mobile network (PLMN), satellite communication (SC) and other fields, the multiple access systems such as direct sequence spread spectrum code division multiple access (DS-CDMA), frequency division multiple access (FDMA), time division multiple access (TDMA), space division multiple access (SDMA), packet division multiple access (PDMA) and pulse address multiple access (PAMA) are all popular wireless communication technology [1]. For example, in the DS-CDMA system, the multiple users can share the same frequency band to improve the spectrum utilization greatly. However, in the actual communication

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process, there are some issues such as the unsatisfactory spreading code correlation characteristics, uncoordinated signal synchronization, transmission distortion, undesirable cross-correlation and the implementation of the spreading code with zero correlation value, which always cause the phenomenon such as incompletely orthogonal of spreading waveform, and further lead to multiple access interference (MAI), ultimately seriously restrict the capacity and performance of the multiple access communication systems [2].

The interference cancellation multi-user detection technology is an research focus of multiple access mobile communication system, which includes the successive interference cancellation (SIC) [3], the parallel interference cancellation (PIC) [4] and the cascade structure interference cancellation (IC) algorithms [5]. The basic principle of interference cancellation multi-user detection is firstly to estimate the MAI of each user at the receiving terminal, and then eliminate some or all MAI in the received signal [6]. This class detector is generally formed by a multi-level detection structure.

SIC detector gradually reduces the maximum power user-generated interference by the multi-user data decisions of all users, then estimates the user signal source of each detection level, and finally, restructures the load information of each received user signal at the receiving terminal by the signal source estimation results [7]. Because this processing must constantly order the new succession sort of multi-users to priority process the maximum power user, so any sort error would increase MAI and lead detection error diffusion [8]. PIC detector generates the MAI by the decision estimate value of the $m-1$th detection level, then removes it completely in the received signal on the mth level. This processing is good of short processing delay and high detection efficiency [9]. But each detection error on any level would cause unacceptably high complexity, low convergence rate, poorer magnitude estimates and near-far problem (NFP). Because a reliable detection result depends on the accurate amplitude estimation, therefore, the low amplitude estimation accuracy may cause the reduction of system performance gain, and then limit the system performance. In summary, any detection error diffusion on any detection level would severely affect the precision of SIC and PIC detector in the subsequent levels. In addition, when the power control is not satisfactory, as in the multi-path channel, the performance of SIC is better than the performance of PIC. Conversely, the performance of PIC is superior to the performance of SIC. In general, while the SIC has a better detection performance on the weak power user signal, but the processing always reduce the detection performance of the maximum power user [10].

Cascade structure IC detector is a compromise approach between SIC and PIC in the aspects of system delay and performance. Generally, IC detector improves the multi-interference suppression ability by the multi-level cascade structure detection, which adapts phases iteration for all users severally by the same iterative calculation method [11]. Although this processing can effectively avoid detection error diffusion, but the excessive repeated computations always result in high complexity and instability convergence, which heavily limit the project implementation.

Based on the weak decomposition theory, the Schwarz algorithm can achieve the real-time acquisition of weighted norm error convergence rate, then assigns the users power sub-domain boundary value to internal boundary unit by information transfers, and finally, obtains the overall numerical solution of all users in the channel [12].

In this paper, we present a combination of Schwarz and cascade structure IC detection algorithm to achieve the power sub-domain boundary value precise control of user signals, then restrict the generation and diffusion of detection error, finally ensure detection precision and convergence through real-time estimation of channel.

2 MUD Model for Multiple Access Communication System

Assume an asynchronous multiple access communication system with $2P + 1$-length transmitted symbol, the bit interval is T, the user equivalent channel response maximum order is P, and the time sequence is $\{-P, -P + 1, \ldots, -1, 0, 1, \ldots, P - 1, P\}$. Supposing the 1-user is the expected user, let all K users send asynchronous signals in the sum noise channel and add sum noise for each user signal respectively [13]. Then adapt spread spectrum secondary on chaotic sequence and makes power sub-domain boundary value precise control for each user respectively. All of these send signals after been double spread spectrum processing by the asynchronous S hexadecimal transmission mode [13]. The S hexadecimal signal of the k-user is expressed as:

$$\boldsymbol{S} = \{s_{k,0}, s_{k,1}, \ldots, s_{k,S-1}\}, (k = 1, \ldots, K) \tag{1}$$

for all serial number k and i, the sending data of signal transmitting symbol $\{b_k(i)\}$ is independent and identically distributed, the output signal model is expressed as:

$$\begin{cases} y_k = \int_0^T r(t)s_k(t)\mathrm{d}t = A_k b_k(i) + \sum\limits_{i=1, i\neq k}^{K} A_i b_i \rho_{ik} + n_k(t),\ b_k(i) \in \{-1, +1\} \\ \rho_{ik} = T^{-1}\int_0^T s_i(t)s_k(t)\mathrm{d}t,\ n_k(t) = T^{-1}\int_0^T n(t)s_k(t)\mathrm{d}t,\ t \in [iT, (i+1)T] \end{cases} \tag{2}$$

where: A_k is the amplitude of the received signal; ρ_{ik} is the spread spectrum inter symbol correlation coefficient; $s_k(t)$ is the characteristic waveform; $n_k(t)$ is the noise-related output of AWGN.

Generally, the tradition SIC and PIC algorithm process MAI as the background noise, then detect the output of the matched filter (MF) detector directly as $\hat{b}_k = \mathrm{sgn}(y_k)$, which easily increase bit error rate (BER) and reduce the system capacity.

When $t \notin [0, T]$, then $s_k(t) = 0$, if the energy characteristic waveform is limited to $t \in [0, T_C]$, the characteristic waveform is:

$$\begin{cases} s_k(t) = \sum\limits_{l=0,\, l\in\{-L,L\}}^{N-1} s_{k,l} P_{T_C}(t - lT_C) \Leftrightarrow \int_0^T s_k^2(t)\mathrm{d}t = 1 \\ \|s_k\|^2 = \int_0^T s_k(t)\mathrm{d}t = 1,\ P_{T_C}|_{t\in[0,T_C]} = 1/\sqrt{T_C},\ T_C = T/N \end{cases} \tag{3}$$

where: N is the spread spectrum processing gain; $\{s_{k,0}, s_{k,1}, ., s_{k,N-1}\}$ is the normalized spectrum sequence ($\pm N^{-1/2}$); P_{T_C} is the T_C-cycle matrix code piece.

Because MAI can be equivalent to the pseudo-random (PN) sequence signal with a strong correlation structural, and the correlation function between each user is known [14]. Therefore, we can use the structural information and statistics information of these PN sequence to eliminate MAI and thus improve the system performance. The PN sequence generator is defined as:

$$\begin{cases} PN(z) = 1 + PN_1 z + \ldots + PN_{K-1} z^{m-1} + z^m \\ b_k[m] = \sum_{1}^{K} b_k(m) PN_k = \boldsymbol{U}(\boldsymbol{V}^{\mathrm{T}}) = [b_1, b_2, \ldots, b_K][PN_1, PN_2, \ldots, PN_m]^{\mathrm{T}} \\ \boldsymbol{U} = [b_1, b_2, \ldots, b_K], \boldsymbol{V} = [PN_1, PN_2, \ldots, PN_m], L_{PN\max} = 2^m - 1, \end{cases} \quad (4)$$

where: $L_{PN\max}$ is the maximum cycle of the PN sequence generator; $\boldsymbol{U}$ is the state vector of shift register; $\boldsymbol{V}$ is the connect vector; $b_k[m]$ is the feedback signal outputted by modulo-two adder.

The PN sequence generator and the corresponding results (one sample per symbol) of PN sequence generator are shown in Figs. 1 and 2.

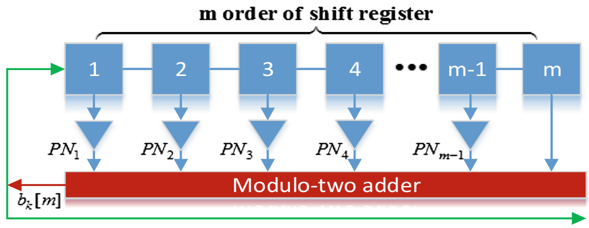

Fig. 1. PN sequence generator

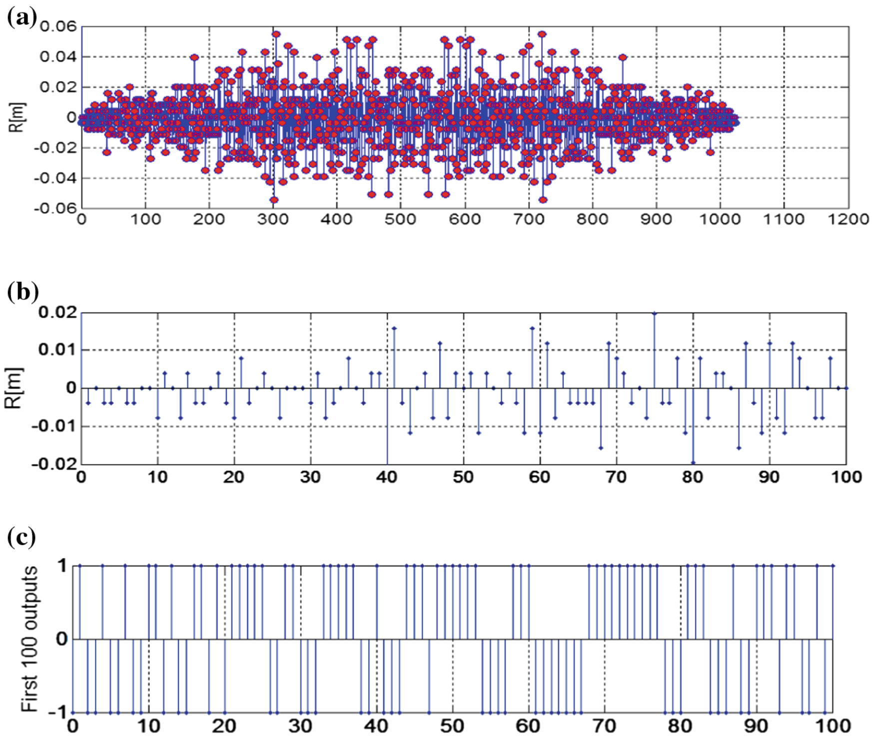

Fig. 2. (a) The single result of each PN sequence generator unit. (b) The corresponding results of PN sequence generator. (c) The first 100 outputs

Supposing the system noise $e_k(t)$ of the k-th user is equivalent to the sum of AWGN component $n_k(t)$ and zero mean colored noise component $\zeta_k(t)$ as:

$$\begin{cases} e_k(t) = n_k(t) + h_k\zeta_k(t) \\ e_k(n,i) = e(nL+i) \end{cases} \tag{5}$$

where: h_k is the colored noise intensity; $e(n,i)$ is the sum sequences noise component, and $e(n,i) = e(nL+i)$.

At the receiving terminal, the received signal after dealing with adaptive filter and binary phase shift keying (BPSK) modulate can be equivalent as follow:

$$r(t) = \sum_{k=1}^{K}\{\sum_{i=-\infty}^{\infty}[A_k b_k(i) s_k(t-iT-\tau_k) + \ p_k(t-iT-\tau_k)]\cos(\omega_k t) + e_k(t)\} \tag{6}$$

where: $p_k\ (\pm 1)$ is the waveform of the secondary spread spectrum; T is the bit interval; τ_k is the time delay; $\boldsymbol{\omega}_{Ck}$ is the adaptive weight vector of filter unit.

Generally, short (cycle) spreading sequence is commonly used in direct sequence spread spectrum signal model systems, namely, the spreading sequence cycle of each user is equal to the corresponding symbol cycle.

However, in the actual mobile communication transmission conditions, especially for the multiple access communication systems, it often appears phenomenon as the spreading sequence cycle is greater than the symbol cycle (long spread). Replacing $s_k(t-iT-\tau_k)$ by $s_{k,(i)_Q}(t-iT-\tau_k)$, the received signal model on Eq. 3 is:

$$s_{k,(i)_Q}(t) = \sum_{l=0}^{N-1} s_{k,[i/Q]N+l} P_{T_c}(t-lT_c) \tag{7}$$

where: $(i)_Q$ is $i \mod Q$ operation; $l \in [0,L]$, $L > N$ and $[\bullet]$ is the end function; L is the long spread spectrum sequences cycle, satisfy as $L/N \triangleq Q > 1$.

The element of time-shift characteristic waveform cross-correlation matrix $\boldsymbol{R}(l)$ for the i-th and k the user can defined as:

$$\boldsymbol{R}_{i,k}(l)|_{\boldsymbol{R}(-l)=\boldsymbol{R}^{\mathrm{T}}(l)} = \int_{-\infty}^{\infty} s_i(t-\tau_i)s_k(t+lT-\tau_k)\mathrm{d}t \triangleq \rho_{ik}(l) \tag{8}$$

then $\boldsymbol{R}(l)|_{l\notin\{-1,0,1\}} = 0$ and $\boldsymbol{R}(-l) = \boldsymbol{R}^{\mathrm{T}}(l)$.

Set the received signal sampling rate is equal to chip rate, $\boldsymbol{r}$ is the output vector of L-dimensional match filter in symbol interval T. So the vector form of asynchronous multiple access communication system base band received signal model is formed as:

$$\begin{cases} \boldsymbol{r} = \sum_{k=1}^{K} \boldsymbol{A}_k \boldsymbol{b}_k \boldsymbol{s}_k \boldsymbol{p}_k + \boldsymbol{e} \\ \boldsymbol{p} = [\boldsymbol{p}_1, .., \boldsymbol{p}_K]^{\mathrm{T}}, \boldsymbol{p}_k = L^{-1}[p_1^k, .., p_L^k]^{\mathrm{T}} \end{cases} \tag{9}$$

$$\begin{cases} \boldsymbol{y} = \boldsymbol{RAb} + \boldsymbol{n} = [y_1, y_2, \ldots, y_K]^{\mathrm{T}} \\ \boldsymbol{R} = E[\boldsymbol{pp}^{\mathrm{T}}], \boldsymbol{A} = \mathrm{diag}[\boldsymbol{A}_1, ., \boldsymbol{A}_K]^{\mathrm{T}} \end{cases} \tag{10}$$

where: $E\{\boldsymbol{nn}^{\mathrm{T}}\} = \sigma^2 \boldsymbol{R}, \boldsymbol{e}$ is the zero mean sum noise covariance matrix.

In any relevant transmission interval, when $\max\{\tau_k\} \leq T$, estimates the bit symbols of transmitted user signals in any relevant transmission interval, then the asynchronous multiple access communication system with K users could be equivalent to a synchronous user multiple access communication system with $2K - 1$ users [15]. If $2K - 1 \leq L$ and all spreading code of the $2K - 1$ users are linearly irrelevant, the calculation of asynchronous system is similar to synchronization system.

3 Schwarz-IC Algorithm

The computing structure of S-IC algorithm is different from the traditional serial pattern detector. Every SIC unit of S-IC detector is formed by a traditional serial processing unit and a Schwarz boundary value control unit, this structure can effectively reduce the exception errors of sorting process. The asynchronous Schwarz algorithm takes advantage of the parallel computing of PIC detector. Due to the introduction of Schwarz unit, the single-level PIC unit can determine whether to continue operation according to the latest information variables without waiting for any data input at any time. This combination treatment can significantly reduce the computational complexity caused by excessive duplicate detection.

3.1 Schwarz Rules and Implementation Conditions

Define sets: $\boldsymbol{L}^2(0,1) = \{\boldsymbol{q}(x)|\boldsymbol{q}(x), \boldsymbol{q}(x) \in (0,1)\}$ $\boldsymbol{X} = \{\boldsymbol{q}(x)|\boldsymbol{q}(x), \boldsymbol{q}'(x) \in \boldsymbol{L}^2(0,1)\}$, here $q(x)$ is the square-integrable observation function In the interval as (0, 1), and $\boldsymbol{q}$ (1) = 0. Supposing $u(x)$ is the decreasing function. For the one-dimensional boundary value control, which can be equivalent to the power control process problem as:

$$\begin{cases} -\frac{\mathrm{d}}{\mathrm{d}x}[\boldsymbol{k}(x)\frac{\mathrm{d}\boldsymbol{u}}{\mathrm{d}x}] = f(x) \\ 0 < x < 1,\ \boldsymbol{u}(0) = 0,\ \boldsymbol{u}'(1) = 0 \end{cases} \tag{11}$$

if $\boldsymbol{p} = k(x)\frac{\mathrm{d}\boldsymbol{u}}{\mathrm{d}x}$, so $-\frac{\mathrm{d}\boldsymbol{p}}{\mathrm{d}x} = f(x), \quad 0 < x < 1$ so $\boldsymbol{p} - \boldsymbol{k}(x)\frac{\mathrm{d}\boldsymbol{u}}{\mathrm{d}x} = 0$, $\boldsymbol{u}(0) = 0$, $\boldsymbol{p}(1) = 0$, for an arbitrary function $v(x) \in L^2(0,1)$, equivalent integral weak form of Eq. 11 is:

$$\int_0^1 (\frac{\mathrm{d}\boldsymbol{p}}{\mathrm{d}x} + \boldsymbol{f}(x))\boldsymbol{v}\mathrm{d}x = 0 \tag{12}$$

the equivalent integral weak form of Eq. 11 is:

$$\int_0^1 (\boldsymbol{k}^{-1}(x)\boldsymbol{p} - \frac{\mathrm{d}\boldsymbol{u}}{\mathrm{d}x})\boldsymbol{q}\mathrm{d}x = 0 \tag{13}$$

for segment integral boundary condition as $\boldsymbol{u}(0) = \boldsymbol{u}'(1) = 0$, there is:

$$\int_0^1 (\boldsymbol{k}^{-1}(x)\boldsymbol{pq} + \boldsymbol{u}\frac{\mathrm{d}\boldsymbol{p}}{\mathrm{d}x})dx = 0 \tag{14}$$

Equations 15 and 16 are conducive to the finite element approximation. Define a bounded open set: $\Omega \subset \boldsymbol{R}^n$, $\exists \boldsymbol{B}(\boldsymbol{x})$, $(\boldsymbol{B}(\boldsymbol{x}) \geq 0)$ for the continuous Schwarz algorithm. When $\boldsymbol{x} \subset \Omega$, $\boldsymbol{A}_{ij}$ is consistent positive definite. Assume a boundary value problem: $\boldsymbol{Lu}\,|_{\Omega} = \boldsymbol{f}$, $\boldsymbol{u}\,|_{\partial\Omega} = \boldsymbol{g}$, $\boldsymbol{u}\,|_{|\Omega|_{\min}} = \boldsymbol{f}(x,y)$, $\boldsymbol{u}\,|_{|\Omega|_{\min}} = \boldsymbol{g}(x,y)$, then the differential operator can be expressed as:

$$\boldsymbol{Lu} = -\sum_{i,j=1}^{K} \frac{\partial}{\partial \boldsymbol{x}_j}(\boldsymbol{A}_{ij}\frac{\partial \boldsymbol{u}}{\partial \boldsymbol{x}_i}) + \boldsymbol{B}(\boldsymbol{x})\boldsymbol{u} \tag{15}$$

make non-average decomposition for the bounded open set Ω, let $\Omega_i \cap \Omega_j \neq \phi$, $i \neq j$, and $\boldsymbol{H}_{\boldsymbol{g}}^1(\Omega)$ is the boundary maximum approximation matrix, ε is the error-limitation. Parallel compute the sub-domain boundary value under condition of $\boldsymbol{u}^0 \in \boldsymbol{H}_{\boldsymbol{g}}^1(\Omega)$, where $k = 0$, then we have:

$$\begin{cases} \boldsymbol{Lu}_i^{k+1}|_{\Omega_i} = \boldsymbol{f} \\ \boldsymbol{u}_i^{k+1}|_{\partial\Omega_i} = \boldsymbol{u}^k \end{cases}, (i = 1, 2, \ldots, k), \overline{\Omega} = \bigcup_{i=1}^{k \leq K} \bar{\Omega}_i \tag{16}$$

extend the final solution $\boldsymbol{u}_i^{k+1}$ on Ω_i to Ω, so:

$$\bar{\boldsymbol{u}}_i^{k+1} = \begin{cases} \boldsymbol{u}_i^{k+1}, & (\boldsymbol{x}, \boldsymbol{y}) \in \Omega_i \\ \boldsymbol{u}^k, & (\boldsymbol{x}, \boldsymbol{y}) \in \Omega/\Omega_i \end{cases} \tag{17}$$

calculate average value of all sub-domain solutions, so:

$$\boldsymbol{u}_i^{k+1} = \frac{1}{K}\sum_{i=1}^{k \leq K} \bar{\boldsymbol{u}}_i^{k+1} \tag{18}$$

when ε is the approximate solution on $\boldsymbol{u}^{k+1}$, there is $||\boldsymbol{u}^{k+1} - \boldsymbol{u}^k|| \leq \varepsilon$.

3.2 The Algorithm Implementation of Basic IC Cascade Multi-user Detection

In the multi-path fading channel, supposing $\boldsymbol{c}_k(i)$ is the decision vector, $\boldsymbol{c}_{\mathrm{opt}}$ is the optimal decision vector, $\boldsymbol{\omega}_{Ck}$ is the adaptive weight vector of each filter unit is also the adaptive update component of $\boldsymbol{c}_k(i)$, $\boldsymbol{\omega}_{\mathrm{opt}}$ is the weight vector of $\boldsymbol{c}_{\mathrm{opt}}$, $g_k(i)$ is the equivalent channel response, $\{\boldsymbol{c}_k(i)\}_{l=0}^{L-1}$ is L-length spread spectrum code, and $\boldsymbol{e}_{\mathrm{optk}}(i)$ is sun noise vector. The process equation of expected user is formed as:

$$\boldsymbol{\omega}_{\text{opt1}}(i+1) = \boldsymbol{\omega}_{\text{opt1}}(i) \tag{19}$$

where: $\boldsymbol{\omega}_{\text{pot1}}(i)$ is the new dynamic state vector.

The observation equation of expected user is formed as:

$$\boldsymbol{y}_1(i) = \boldsymbol{d}_k^{\text{T}}(i)\boldsymbol{\omega}_{\text{opt1}}(i) + \boldsymbol{e}_{\text{opt 1}} \tag{20}$$

where: $\boldsymbol{d}_k^{\text{T}}(i)$ is a $R-1$-dimensional row vector; R is the user symbols coherence length ($R = [(L+P-1)/L]$).

The dynamic system process equation is formed as:

$$\begin{cases} \boldsymbol{x}_k(i+1) = \boldsymbol{F}_k(i+1,i)\boldsymbol{x}(i) + \boldsymbol{e}_{\text{opt1}} \\ \boldsymbol{e}_{\text{opt1}}(i) \equiv 0 \end{cases} \tag{21}$$

where: $\boldsymbol{x}_k(i)$ is the $L \times 1$ state vector in the i-th moment; $\boldsymbol{F}_k(i+1,i)$ is a known $L \times L$ state transfer matrix.

The dynamic system observation equation is formed as:

$$\begin{cases} \boldsymbol{y}_k(i) = \boldsymbol{C}_k(i)\boldsymbol{x}_k(i) + \boldsymbol{\varepsilon}_{k+1}(i) \\ \boldsymbol{y}_k(i) \Rightarrow \vec{y}_k(i), \boldsymbol{\varepsilon}_2(i) \Rightarrow e_{\text{opt1}}(i),\ \boldsymbol{C}_k(i) \Rightarrow \boldsymbol{d}_k^{\text{T}}(i) \end{cases} \tag{22}$$

where: $\boldsymbol{y}_k(i)$ is a $R \times 1$-dimensional state vector of system in the i-th moment; $\boldsymbol{C}_k(i)$ is a $R \times L$-order measurement matrix; $\boldsymbol{\varepsilon}_{k+1}(i)$ is the error of measurement matrix.

Because $\boldsymbol{F}_k(i+1,i)$ is a $L \times L$-order unit matrix $\boldsymbol{I}$, so after through the channel fading, the spread spectrum code signal can be converted as:

$$\begin{cases} d_k(i) = c_k(i) * g_k(i) = \sum\limits_{p=0}^{P-1} g_k(p)c_k(i-p) \\ i = 0, \ldots., L+p+1; p \in [0,P] \end{cases} \tag{23}$$

the r-th sampling of the received base band signal in i-th symbol period is:

$$\begin{cases} x_k(r,i) = x_k(rL+i) = \sum\limits_{k-1}^{K}\sum\limits_{r=0}^{R-1} A_k d_k(r,i) b_k(i-r) \\ i = 0, \ldots, L-1; d_k(r,i) = d_k(rL+i) \end{cases} \tag{24}$$

the L samples in the i-th symbol periods can be represented as a $L \times 1$-order matrix:

$$\begin{cases} \boldsymbol{x}_k(i) = \boldsymbol{A}\boldsymbol{d}_1 b_k(i) + \boldsymbol{D}_{\text{int}}\boldsymbol{d}_{\text{int}k}(i) + \boldsymbol{e}_k(i) + \boldsymbol{\varepsilon}_{k+1}(i) \\ E[\boldsymbol{e}_k(i)\boldsymbol{e}(i)^{\text{H}}] = \sigma_e^2 \boldsymbol{I}_L, \boldsymbol{e}_k(i) = [e_k(i,0), ., e_k(i,L-1)]^{\text{T}} \end{cases} \tag{25}$$

where: $\boldsymbol{D}_{\text{int}}$ is interference matrix contains ISI and MAI; $\boldsymbol{d}_{\text{int}k}$ is the interference symbol vector.

Set a L-dimensional decision vector $\boldsymbol{f}(k)$ for expected user, the MUD model is:

$$\widehat{b}_1(i) = \operatorname{sgn}(<\boldsymbol{f}_k(i), \boldsymbol{x}_k(i)>) \tag{26}$$

supposing the iterative initial condition is $\boldsymbol{W}_k(1,0) = \boldsymbol{I}$, for the expected user, the iterative calculation of S-IC is:

$$\begin{cases} g_k(i) = \boldsymbol{W}_k(i,i-1)d_k(i)\{\boldsymbol{d}_k^{\mathrm{H}}(i)\boldsymbol{W}_k(i,i-1)\boldsymbol{d}_k(i) + \xi_{\min}\}^{-1} \\ \boldsymbol{W}_k(i+1,i) = \boldsymbol{W}_k(i,i-1) - g_k(i)\boldsymbol{d}_k^{\mathrm{H}}(i)\boldsymbol{W}_k(i,i-1) \\ \widehat{\boldsymbol{\omega}}_{\mathrm{opt1}}(i) = \widehat{\boldsymbol{\omega}}_{\mathrm{opt1}}(i-1) + g_k(i)\{\boldsymbol{y}_k(i) - \boldsymbol{d}_k^{\mathrm{H}}(i)\widehat{\boldsymbol{\omega}}_{\mathrm{opt1}}(i-1)\} \\ \boldsymbol{c}_{\mathrm{opt1}}(i) = \boldsymbol{S}_1 - \boldsymbol{C}_{1,i}\hat{\boldsymbol{\omega}}_{\mathrm{opt1}}(i) \\ \xi_{\min} = \operatorname{cov}\{\boldsymbol{e}_{\mathrm{opt}k}\} = F(\boldsymbol{e}_{\mathrm{opt1}}^2(i)) = A_1^2 + \varepsilon_{\min} \end{cases} \tag{27}$$

where: $\varepsilon_{\min}$ is the minimum mean square error of the optimal decision vector; $\xi_{\min}$ is minimum output energy; $\boldsymbol{S}_1$ is the S scale received signal of expected user.

So, the dynamic system equation of expected user is:

$$\begin{cases} \widehat{\tilde{x}}_1 = \boldsymbol{F}_1^{\mathrm{H}}(i)\boldsymbol{\omega}_1(i) + \boldsymbol{e}_2(i) + \boldsymbol{\varepsilon}_2(i) \\ \boldsymbol{\omega}_1(i) = \boldsymbol{\omega}_1(i-1) + \Delta\boldsymbol{\omega}_1(i-1) \\ \tilde{\boldsymbol{x}}_k(i) = \boldsymbol{s}_k^{\mathrm{H}}\boldsymbol{x}_k(i) \\ \boldsymbol{F}_1^{\mathrm{H}}(i) = \boldsymbol{x}_1^{\mathrm{H}}(i)U_{null} \\ \boldsymbol{\varepsilon}_2(i) = \boldsymbol{c}_{\mathrm{opt1}}^{\mathrm{H}}\boldsymbol{x}(i) \end{cases} \tag{28}$$

where: $\tilde{\boldsymbol{x}}_k(i)$ is the observation vector; $\boldsymbol{F}_1^{\mathrm{H}}(i)$ is the system observation matrix of expected user; $\boldsymbol{e}_2(i)$ is the observation noise matrix.

Because both the number of activity users and noise characteristics are time-varying, the traditional SIC, PIC and IC detector always lead detection divergence or abnormal filtering, which reduces the detection accuracy. So, it is necessary to improvement of iterative calculation processing for traditional interference cancellation algorithm. Estimate the adaptive update section $\boldsymbol{\omega}_1(i)$ of $\boldsymbol{c}_{\mathrm{opt1}}(i)$ by Schwarz algorithms rules and let it to be the tap weight vector of expected user. Set m is the number of Schwarz iteration, let i and m unified, $\boldsymbol{\delta}$ is the corresponding vector forgetting factor, so we have:

$$\begin{cases} \boldsymbol{\omega}_1[m] = \boldsymbol{\omega}_1[m|m-1] + \boldsymbol{K}[m]\boldsymbol{\delta}[m] \\ \boldsymbol{\omega}_1[m|m-1] = \boldsymbol{\omega}_1[m-1] + \boldsymbol{q}[m-1] \\ \boldsymbol{\delta}_k[m] = \tilde{\boldsymbol{x}}_k[m] - \boldsymbol{F}_k^{\mathrm{H}}[m]\boldsymbol{\omega}_1[m|m-1] - \boldsymbol{r}[m-1] \\ \boldsymbol{r}_k[m] = \{\boldsymbol{I} - \boldsymbol{d}_k[m-1]\}\boldsymbol{r}_k[m-1] + d_{m-1}\{\tilde{\boldsymbol{x}}_k[m] - \boldsymbol{F}_k^{\mathrm{H}}[m]\boldsymbol{\omega}_1[m|m-1]\} \\ \boldsymbol{R}_k[m] = (1-d_{m-1})\boldsymbol{R}_k[m-1] \\ \qquad + d_{m-1}\{\boldsymbol{\delta}_k[m]\boldsymbol{\delta}_k^{\mathrm{T}}[m] - \boldsymbol{F}_k^{\mathrm{H}}[m]\boldsymbol{P}_k[m|m-1]\boldsymbol{F}_k[m]\} \end{cases} \tag{29}$$

So the Schwarz iteration rule is as follows:

$$\begin{cases} \boldsymbol{\omega}_k(i) = \boldsymbol{\omega}_k(i|i-1) + \boldsymbol{W}_k(i)\delta_k \\ \qquad = \boldsymbol{\omega}_1(i-1)[\boldsymbol{I} - \boldsymbol{W}_k(i)\boldsymbol{F}_k^{\mathrm{H}}(i)] + \boldsymbol{q}_k(i-1)[\boldsymbol{I} + \boldsymbol{W}_k(i)\boldsymbol{F}_k^{\mathrm{H}}(i)] \\ \qquad + \boldsymbol{W}_k(i)[\widehat{\boldsymbol{x}}_k(i) - \boldsymbol{r}_k(i-1)] \\ \boldsymbol{q}_k(i) = (1-\delta_{k-1})\boldsymbol{q}_k(i-1) + \delta_{k-1}[\boldsymbol{\omega}_1(i) - \boldsymbol{\omega}_1(i-1)] \end{cases} \tag{30}$$

$$\begin{cases} \boldsymbol{r}_k(i) = (\boldsymbol{I} - \boldsymbol{d}_{k-1})\boldsymbol{r}_k(i-1) + \delta_{k-1}[\widehat{\boldsymbol{x}}(k) - \boldsymbol{F}_k^{\mathrm{H}}(i)\boldsymbol{\omega}_1(i|i-1)] \\ \boldsymbol{W}_k(i) = \frac{\boldsymbol{P}_k(i|i-1)\boldsymbol{F}_k(i)}{\boldsymbol{F}_k^{\mathrm{H}}(i)\boldsymbol{P}_k(i|i-1)\boldsymbol{F}_k(i) + \boldsymbol{R}_k(i-1)} \\ \boldsymbol{R}_k(i) = (1-\delta_{k-1})\boldsymbol{R}_k(i-1) + \boldsymbol{d}_{k-1} - \delta_{k-1}\boldsymbol{F}_k^{\mathrm{H}}(i)\boldsymbol{P}_k(i|i-1)\boldsymbol{F}_k(i) \\ \boldsymbol{P}_k(i) = [\boldsymbol{I}_R - \boldsymbol{W}_k(i)\boldsymbol{F}_k^{\mathrm{H}}(i)]\boldsymbol{P}_k(i|i-1) \\ \boldsymbol{P}_k(i|i-1) = \boldsymbol{P}_k(i-1) + \boldsymbol{Q}_k(i-1) \\ \boldsymbol{Q}_k(i) = (1-\boldsymbol{d}_{k-1})\boldsymbol{Q}_k(i-1) + \boldsymbol{d}_{k-1} + \boldsymbol{d}_{k-1}\boldsymbol{P}_k(i)\boldsymbol{P}_k(i-1) \end{cases} \tag{31}$$

where: $\delta_{k-1} = (1-b)/(1-b^k)$, $0 < b < 1$, Q is the $K \times (2P+1)$-dimensional processing boundary conditions of square-integrable observation function, (k, i)-element in Q is $q_k(i)$.

3.3 The Successive and Parallel Detection Units of Schwarz-IC Cascade Process Implementation

The improved SIC and PIC unit single-stage structure of S-IC detector for the multiple access communication system are shown in Figs. 3 and 4.

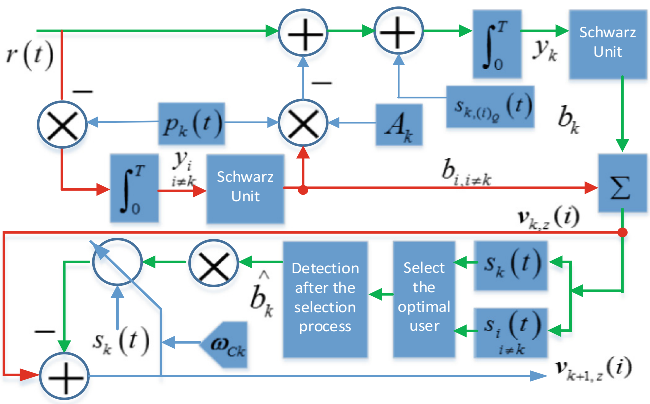

Fig. 3. Single-stage structure of S-IC processing

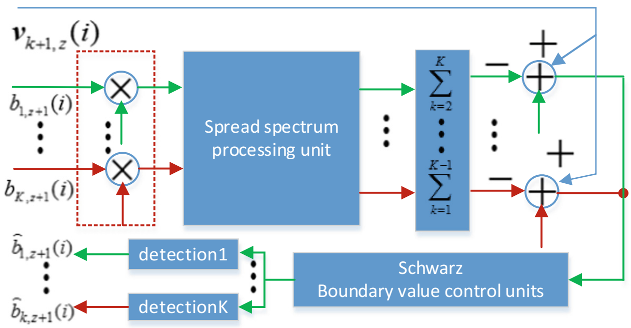

Fig. 4. Single-stage structure of S-IC processing

The improved structure of S-IC detection unit can use the relevant information of observational data to estimate the properties of time-varying unknown noise statistics real-time while conducting state filtering. Set $\boldsymbol{y}_k$ is the actual output vector of filter, $\boldsymbol{v}_k(i)$ is the input vector, $\boldsymbol{u}_k(i)$ is the energy input vector of S-IC unit, $\boldsymbol{g}_k(i)$ is the expected response vector, and μ is the step parameter, so

$$\begin{cases} \boldsymbol{v}_k(i) = \boldsymbol{d}_k(i) + \boldsymbol{g}_k(i) - \boldsymbol{\omega}^{\mathrm{H}}_{\mathrm{opt}k}(i)\boldsymbol{u}_k(i) \\ \boldsymbol{\omega}_k(i+1) = \boldsymbol{\omega}_{\mathrm{opt}k}(i) + \mu\boldsymbol{u}_k(i) * \boldsymbol{v}_k(i) \end{cases} \tag{32}$$

after dealing with double spread spectrum, the signal output of k-user in the z-th (z is an integer greater than 1) detection level of traditional S-IC detector can be formed as:

$$b_{k,z}(i) = \mathrm{sign}[\boldsymbol{S}_k^{\mathrm{T}}\boldsymbol{v}_{k,z}(i)] \tag{33}$$

the maximum power user is expressed as:

$$r_{\max}(t) = \arg\max_{1\le k\le K}\{|\boldsymbol{S}_k^{\mathrm{T}}\boldsymbol{v}_{k,z}(i)|\} = \arg\max_{1\le k\le K}\{|[s_{k,0},.,s_{k,K-1}]\boldsymbol{v}_{k,z}(i)|\} \tag{34}$$

where: $\boldsymbol{S}_k$ is S band asynchronous spread spectrum code after double spread spectrum.

On the z-th detection level, $\boldsymbol{v}_{1,z}(i) = \boldsymbol{r}(t)$, detected signal $b_{k,z}(i)$ can be changed as:

$$\boldsymbol{v}_{k+1,z}(i) = \boldsymbol{v}_{k,z}(i) - \boldsymbol{\omega}_{\mathrm{opt}k}(i)b_{k,z}(i)\boldsymbol{S}_k \tag{35}$$

the weight for the detector after through adaptive filter detection unit is adjusted as:

$$\boldsymbol{\omega}_k(i+1) = \boldsymbol{\omega}_k(i) + 2\mu\boldsymbol{v}_{k,z}(i)b_{k,z}(i)\boldsymbol{S}_k \tag{36}$$

According to Eq. 9, the received PIC signal vector is expressed as:

$$\begin{cases} \boldsymbol{r}(t) = \boldsymbol{S}(t,Q)\boldsymbol{P}(t,Q) + \boldsymbol{e} \;\Rightarrow \boldsymbol{r} = \sum_i \sum_{k=1}^{K} \boldsymbol{A}_k\boldsymbol{b}_k^{(i)}\boldsymbol{s}_k\boldsymbol{p}_k + \boldsymbol{e} \\ \boldsymbol{S}(t,Q) = \sum_i \sum_{k=1}^{K} \boldsymbol{s}_{k,q(i)}(t - iT - \tau_k) \\ \boldsymbol{P}(t,Q) = \sum_i \sum_{k=1}^{K} p_{k,q(i)}(t - iT - \tau_k) \end{cases} \tag{37}$$

the estimated value of $\boldsymbol{b}$ on the z-th PIC level is:

$$\widehat{\boldsymbol{b}}_{k,z}(i) = [\widehat{b}_{1,z}(i), \widehat{b}_{2,z}(i), .., \widehat{b}_{K,z}(i)]^{\mathrm{T}} \tag{38}$$

the information bit on the z + 1-th IC level is:

$$\begin{cases} \widehat{b}_{k,z+1}(i) = \arg\{\max\limits_{\substack{q_k \in (-1,1) \\ q_i = b_k(i), \forall \neq k}} [2\boldsymbol{y}^{\mathrm{T}}\boldsymbol{b} - \boldsymbol{b}^{\mathrm{T}}\varphi\boldsymbol{b}]\} = \mathrm{sgn}[\boldsymbol{\phi}_{k,z}(i)] = \mathrm{sgn}[y_k - \sum\limits_{i \neq k} \widehat{b}_{k,z}(i)\varphi_{kl}] \\ \phi_{k,z}(i) = [\phi_{1,z}(i), \phi_{2,z}(i), \ldots, \phi_{K,z}(i)]^{\mathrm{T}} \\ \varphi_{kl} = \int_0^T s_k(t)p_k(t)s_l(t)p_l(t)dt \\ y_k = \int_0^T r(t)s_k(t)p_l(t)dt \end{cases} \tag{39}$$

where: $\phi_{k,z}(i)$ is the z th statistical results; φ_{kl} is the element of correlation matrix φ.

The Schwarz-IC detector re-estimates MAI by the estimated value of $\boldsymbol{b}$ obtained on the m-th detection level, then cancels out the latest produced MAI from $\boldsymbol{y}$, finally obtains the estimated value of $\boldsymbol{b}$ on the m + 1-th detection level. When there is no new user information added in the channel, the IC cascade detection decision process is terminated. Because the signal power and the wireless communications parameters are time-varying, so the introduction Schwarz unit can precise track the channel variation and a single user signal power by the precise control of the user power sub-domain boundary value. Furthermore, it can ensure the accuracy of the interference suppression processing and improve the overall system performance.

4 Simulation Results and Performance Analysis

In a multiple access communication system (Multi-path number P = 10, K users), let each user send an information symbol in multi-path channel in each simulation step (1s), then use m-sequences (The number of sequences is K, N = 31) to make independent spread spectrum and add sum noise processing, while make adding processing in user's order respectively. The K users send asynchronous signal in S band transmission asynchronous after through double spread spectrum processing. Then, use the same K m-sequence to despread the information symbols. Finally, complete the symbol recovery processing of these K users (the symbol number is equal to the transmission time) by the integral decision at receiving terminal and sending terminal (Fig. 5).

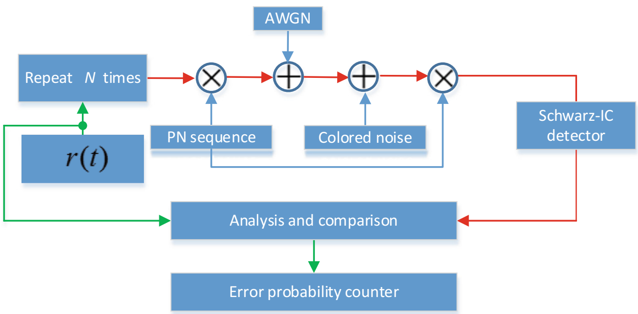

Fig. 5. Multiple access communication spread spectrum system model

set the k-user as the minimum power user, every bit energy is $A_k^2 T/2$. Use Schwarz-IC and SIC detector to detect the excess output energy (EOE) performance of Schwarz-IC, PIC and SIC algorithm. The k-th iterative output signal to interference ratio (SIR) performance on the m-th level of this system is defined as:

$$\mathrm{SIR} = \frac{E^2\{\boldsymbol{c}_{\mathrm{opt}k}^{\mathrm{T}}(n)\boldsymbol{r}\}}{\mathrm{var}\{\boldsymbol{c}_{\mathrm{opt}k}^{\mathrm{T}}(n)\boldsymbol{r}\}} = \frac{A_k^2(\boldsymbol{c}_{\mathrm{opt}k}^{\mathrm{T}}(n)\boldsymbol{p}_k)^2}{\sum_{k=2}^{K} A_k^2(\boldsymbol{c}_{\mathrm{opt}k}^{\mathrm{T}}(n)\boldsymbol{p}_k)^2 + \sigma^2 \boldsymbol{c}_{\mathrm{opt}k}^{\mathrm{T}}(n)\boldsymbol{c}_{\mathrm{opt}k}(n)} \tag{40}$$

the output SIR is defined as:

$$\mathrm{SIR} = \frac{E^2\{\boldsymbol{c}_{\mathrm{opt}k}^{\mathrm{T}}(m)\boldsymbol{r}\}}{\mathrm{var}\{\boldsymbol{c}_{\mathrm{opt}k}^{\mathrm{T}}(m)\boldsymbol{r}\}} = \frac{A_k^2(\boldsymbol{c}_{\mathrm{opt}k}^{\mathrm{T}}(m)\boldsymbol{p}_k)^2}{\sigma^2 \boldsymbol{c}_{\mathrm{opt}k}^{\mathrm{T}}(m)\boldsymbol{c}_{\mathrm{opt}k}(m) + \sum_{k=2}^{K} A_k^2(\boldsymbol{c}_{\mathrm{opt}k}^{\mathrm{T}}(m)\boldsymbol{p}_k)^2} \tag{41}$$

the BER is defined as:

$$\begin{cases} \mathrm{BER} = \phi(\sqrt{e_k(\sigma)\sigma^{-2}}) = \frac{1}{\sqrt{2\pi}} \int_{\sqrt{e_k(\sigma)\sigma^{-2}}}^{\infty} \ln(-\frac{u^2}{2})\mathrm{d}u \\ \phi(j) = \frac{1}{\sqrt{2\pi}} \int_j^{\infty} \ln(-\frac{u^2}{2})\mathrm{d}u \end{cases} \tag{42}$$

where: $e_k(\sigma)$ is the equivalent effective noise energy of the k-th user; ϕ is the conversion function.

EOE is defined as the excess energy of transmitted user signal in order to achieve single-user error performance for MUD algorithm in the mobile communication system, namely the more stable and rapidly for the EOE decay, the more stable the system transmission performance is. The EOE is defined as:

$$\mathrm{EOE} = \xi(m) - \xi_{\min} = \mathrm{MOE}[x_k(m)] - (A_1^2 + \varepsilon_{\min}) \tag{43}$$

Use spreading sequence adapts GOLD sequence, source adapts BPSK signal, step size is $\mu = 0.0005$, the sampling rate is equal to the chip rate. The difference power value between the maximum user and the minimum user is 8 dB, the BER is defined as:

$$P_k(\sigma) = Q\sqrt{e_k(\sigma)\sigma^{-2}} \tag{44}$$

where: $e_k(\sigma)$ is the equivalent energy of the kth user.

4.1 SIR Performance Comparison Analysis

Set K users with different power values. Assume there are no addition and no withdrawal of existing users in the process of the whole communication. Add a set of users with lager power when the iteration number is 600, then withdraw these users and a part of original user when the iteration number is 1200. This program simulate the actual dynamic mobile communication environment.

As shown in Fig. 6: In the multi-user static static conditions, when the iteration number is greater than 400, the SIR performance of S-IC algorithm is significantly better than SIC and PIC algorithm. So S-IC algorithm is of faster convergence rate and

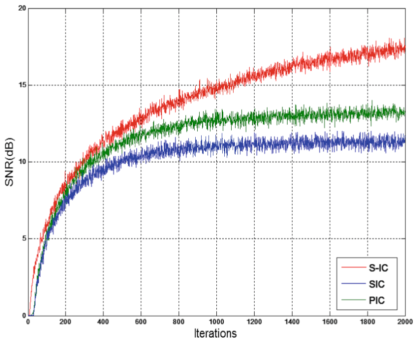

Fig. 6. The static SIR performance analysis

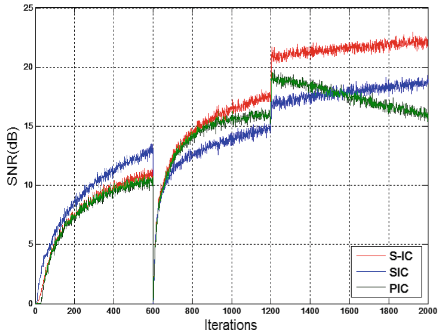

Fig. 7. The dynamic SIR performance analysis

stronger multi-user interference inhibition ability in static condition.

As shown in Fig. 7: In the multi-user dynamic conditions, when there is new interference added in the system (the iteration number is 600), the SIR curve of S-IC and SIC algorithm just appear little bit down peak and recover fast at a high speed before the interference been receded, then basically restore stability convergence after the interference been receded (the iteration number is greater than 1200), while the SIR performance of S-IC algorithm is significantly better than SIC algorithm in the whole process. But the SIR curve of PIC algorithm appears a great attenuation volatility and even becomes unstable convergence after the interference is withdrawn. So S-IC is of better dynamic tracking performance than SIC and PIC algorithm.

4.2 BER Performance Analysis

As shown in the Fig. 8: In the multi-user static conditions, the blind adaptive Schwarz-IC is of better BER performance, namely the new detector can effectively inhibit the interference of strong NFP and improve the detection precision. So Schwarz-IC is of better MAI rejection ability, and MUD ability.

As shown in the Fig. 9: In the dynamic conditions, the S-SIC algorithm is of better BER performance, namely the new detector can effectively inhibit the interference of strong NFP and improve the detection precision. So S-SIC is of better MAI rejection ability, and MUD ability.

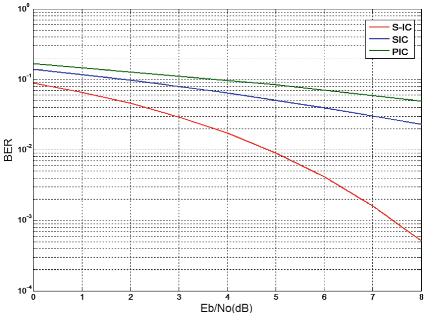

Fig. 8. The static BER performance analysis

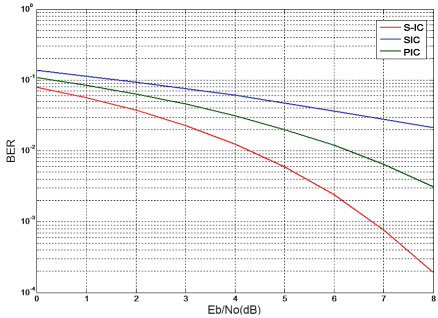

Fig. 9. The dynamic BER performance analysis

4.3 EOE Performance Analysis

As shown in Fig. 10: In the multi-user static conditions, the EOE curve of SIC algorithm appears a great instability fluctuations when the interference brought into the system and recover very slow at a low speed before the interference users been receded while basically higher than 0.1 dB. The EOE of PIC appears serious divergence after the interference brought into the system and ultimately failed to converge. The EOE of S-IC start remarkable convergence before the interference been receded and basically lower than 0.1 dB, final attenuate close to 0 dB value theory. So S-IC is of better interference rejection capability, convergence stability and MUD ability.

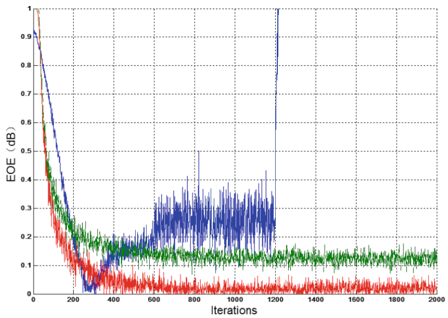

Fig. 10. The static EOE performance analysis

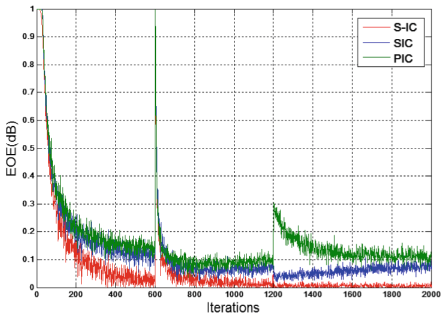

Fig. 11. The dynamic EOE performance analysis

As shown in Fig. 11: In the multi-user dynamic conditions, the EOE curve of SIC algorithm appears a great instability fluctuations when the interference brought into system and recover very slow at a low speed before the interference users been receded while basically higher than 0.1 dB. The EOE of PIC appears serious divergence after the interference brought into system and ultimately failed to converge. The EOE of S-IC start remarkable convergence before the interference been receded and nearly lower than 0.1 dB, final attenuate close to 0 dB value theory. So S-IC algorithm is of better interference rejection capability, convergence stability and MUD ability.

4.4 Error Probability Performance Analysis

As shown in Fig. 12: In the multi-user static conditions, the error probability of SIC algorithm is always higher than 10^{-4}, the error probability of PIC algorithm is always higher than 10^{-5}, furthermore, the decay rate of SIC and PIC algorithm is slower than S-IC algorithm. In contrast, the error probability of S-IC algorithm showed a rapid decay state in the whole detection process and closest to the single-user case. So S-IC algorithm is of better static detection accuracy than SIC and PIC algorithm.

As shown in Fig. 13: In the multi-user dynamic conditions, the error probability of PIC algorithm is always higher than 10^{-2}, the error probability of SIC algorithm is always higher than 10^{-3}, furthermore, like situation in the multi-user static conditions, the decay rate of SIC and PIC algorithm is significantly slower than S-IC algorithm. Although the error probability of S-IC algorithm is slightly worse than the same situation in the multi-user static conditions, there has been no noticeable performance degradation, which still showed a rapid decay and closest to the single-user case. So S-IC algorithm is of better dynamic detection accuracy than others.

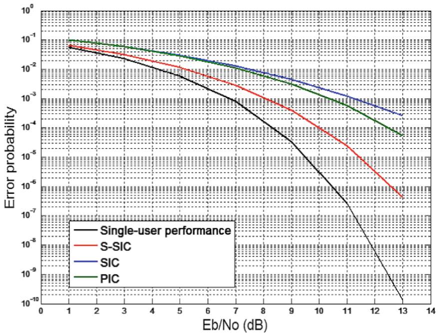

Fig. 12. The static EP performance analysis

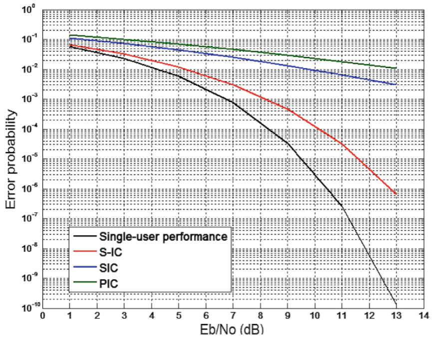

Fig. 13. The dynamic EP performance analysis

5 Conclusion

The Schwarz-IC algorithm can adaptively determine whether to continue operation according to the latest information variables without waiting for data input at any time, while it is helpful for implementation of project. Because there is no system background noise adding in the MAI cancellation processing, the new algorithm can fully track the time-varying channel in complex condition and completely eliminate the co-channel interference. Because it is no need to sort the order of different power user in the MUD processing, so it can effective avoid detection error diffusion caused by the intermediate link detection error of traditional SIC algorithm. Simulation results show that, the Schwarz-IC algorithm outperforms the Schwarz algorithm, PIC algorithm and SIC algorithm in term of BER performance, dynamic tracking capability, convergence and precision control capability. Therefore, the blind adaptive Schwarz-IC MUD algorithm is an efficient MUD scheme.

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