Near-Optimum Multiuser Detectors Using Soft-Output Ant-Colony-Optimization for the DS-CDMA Uplink

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***Abstract*—In this contribution, a novel soft-output ant colony optimization (SO-ACO)-based multiuser detector (MUD)—namely the MUlti-input-Approximation (MUA) assisted SO-ACO-based MUD—is proposed for the synchronous direct-sequence code-division-multiple-access (DS-CDMA) uplink (UL). The previously proposed conventional ACO based MUDs were unable to provide soft log-likelihood ratio (LLR) values for the channel decoder. Hence, to solve this open problem, we commence by proposing the MAximum-Approximation (MAA) assisted SO-ACO algorithm, leading to a novel MUA assisted SO-ACO algorithm, which subsumes the MAA algorithm as a particular case and outperforms the MAA algorithm. More explicitly, at a signal-to-noise ratio (SNR) of 13 dB, the BER performance of the convolutional coding (CC) aided CDMA UL employing the MAA SO-ACO is improved from $5.2 \cdot 10^{-6}$ to $2.7 \cdot 10^{-6}$ by employing the MUA SO-ACO. Our numerical results also demonstrate that the MUA assisted SO ACO-MUD is capable of approaching the optimum performance of the Bayesian detector, when $K = 32$ UL users are supported with the aid of 31-chip Gold codes, while the complexity of the former is a fraction of 10^{-8} lower than that of the latter.**

***Index Terms*—Ant-colony optimization, DS-CDMA, low-complexity near-maximum-likelihood detection, uplink detection.**

I. Introduction

ANT colony optimization (ACO) was first invoked by Colorni *et al.* [1] in 1991 and has recently been applied to near-maximum likelihood (ML) multiuser detection (MUD) aided multiple access (MA) systems [2]–[5]. The ACO-based MUDs [2]–[5] are reported to be able to achieve a lower BER as well as a lower complexity than the genetic algorithm (GA)-based MUDs of [6]. However, most of the ACO-based MUD schemes found in the open literature at the time of writing are only capable of providing hard-decision outputs for the channel decoder. Against this background, an MAximum-Approximation (MAA) aided SO-ACO algorithm has been proposed in [7]. In this contribution, we develop this solution further to the MUlti-input Approximation (MUA) algorithm, which subsumes the above-mentioned MAA algorithm as a special case, associated with a single input. Our simulation results will demonstrate that increasing the number of inputs provided for the MUA algorithm has significantly improved the achievable BER performance compared to that of the MAA SO-ACO algorithm, approaching the single-user performance, at a fraction of the Bayesian detector's complexity.

The rest of this letter is organized as follows. The model of the SO ACO assisted DS-CDMA UL system will be characterized in Section II. In Section III, our new SO ACO-MUD algorithms are detailed and their complexity is characterized. Our simulation results will be provided in Section IV. Finally, we will conclude our discourse in Section V.

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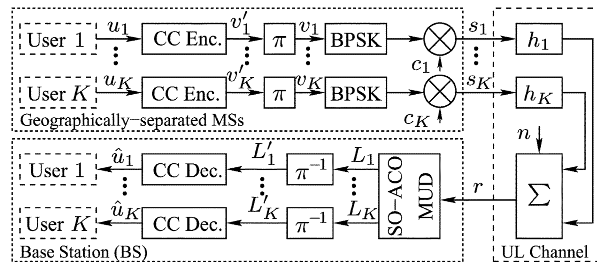


Fig. 1. Schematic of the soft-output ACO assisted DS-CDMA UL transceiver, where K users are supported.

II. System Description

Fig. 1 shows the DS-CDMA UL system model, where each of the K mobile station (MS) transmitters and the base station (BS) receiver employ a single transmit and receive antenna. The kth user's N_u-bit data sequence $\{u_k[i]; i = 1, \ldots, N_u\}$ is firstly channel encoded with a convolutional code (CC) at a rate of $R_c = N_u/N_c$, yielding the coded sequence $\{v'_k[i]; i = 1, \ldots, N_c\}$. After being interleaved by the random bit interleaver π of Fig. 1, each bit of the sequence is then spread employing a user-specific N_s-chip DS spreading sequence waveform $c_k(t)$. Then, the DS-spread signal is binary-phase-shift-keying (BPSK) modulated and transmitted over a single-path flat Rayleigh fading channel h_k, which is assumed to be constant over a symbol duration. Thus, during a symbol interval, the base-band equivalent received signal vector corresponding to the signals received during the N_s chip intervals can be expressed as $\mathbf{r} = \mathbf{CHv} + \mathbf{n}$, where the base-band equivalent received signal vector $\mathbf{r}$, the CHannel Transfer Function (CHTF) matrix $\mathbf{H}$, the base-band equivalent transmitted signal vector $\mathbf{v}$ containing a single element for each of the K users, the AWGN vector $\mathbf{n}$, and the Gold-code matrix $\mathbf{C}$ are defined as follows: $\mathbf{r} = [r_1, r_2, \cdots, r_{N_s}]^T$, $\mathbf{H} = \text{diag}[h_1, h_2, \cdots, h_K]$, $\mathbf{v} = [v_1, v_2, \cdots, v_K]^T$, $\mathbf{n} = [n_1, n_2, \cdots, n_{N_s}]^T$, and $\mathbf{C} = [\mathbf{c}_1, \mathbf{c}_2, \cdots, \mathbf{c}_K]$ where $\mathbf{c}_k = [c_{k1}, c_{k2}, \cdots, c_{kN_s}]^T$, for all the $k = 1, 2, \cdots, K$. Note that the elements in $\mathbf{n}$ are realizations of a random Gaussian variable having a mean of zero and a variance of σ_n^2.

III. Soft-Output Ant Colony Optimization-Based Multiuser Detector

A. Hard-Decision ACO-Based MUD

In the search process of each symbol interval, there will be a maximum of N search iterations. During each iteration, each of the M artificial ants will generate a trial vector constituted by K bits. The final search pool $\mathbf{X}$ derived as the output of the N-iteration search process contains x number of different vectors, where we have $x \leqslant x_{\max} = N \times M$. This implies that the final search pool $\mathbf{X}$ hosts only a small fraction of the entire set of $\mathbf{V}$ containing all the 2^K legitimate combinations, which results in a significantly reduced complexity compared to the exhaustive search process carried out by the ML detectors. For more details on the conventional ACO-based MUD, the interested readers are referred to [3]–[5].

B. MUlti-Input Approximation (MUA) SO ACO-MUD

1) Theoretical Background: The soft-bit value expressed in terms of the log-likelihood ratio (LLR) associated with the kth user can be formulated as [9]

$$L_k = \ln \frac{P(v_k = +1|\mathbf{r}, \mathbf{H})}{P(v_k = -1|\mathbf{r}, \mathbf{H})} \tag{1}$$

where $P(v_k = +1|\mathbf{r}, \mathbf{H})$ is the *a posteriori* probability of the kth user's bit being $+1$ based on the observation of the received signal vector $\mathbf{r}$ and the CHTF matrix $\mathbf{H}$. Let us partition the entire legitimate transmit signal set $\mathbf{V}$ into subsets of $\mathbf{V}_k^+$ and $\mathbf{V}_k^-$ according to the polarity of the kth bit of the vector $\mathbf{v}_i \in \mathbf{V}$, for $i = 1, \ldots, 2^K$. In the Bayesian detector, the probability of $P(v_k = \pm 1|\mathbf{r}, \mathbf{H})$ is given by the sum of the *a posteriori* probabilities of all the 2^{K-1} vectors in the set $\mathbf{V}_k^{\pm}$ based on the observation of the received signal vector $\mathbf{r}$ and the CHTF matrix $\mathbf{H}$ [8], which is formulated as

$$L_k^{\mathrm{BAY}} = \ln \frac{\sum_{\tilde{\mathbf{v}}_{k,i}^+ \in \mathbf{V}_k^+} P\left(\tilde{\mathbf{v}}_{k,i}^+ | \mathbf{r}, \mathbf{H}\right)}{\sum_{\tilde{\mathbf{v}}_{k,i}^- \in \mathbf{V}_k^-} P\left(\tilde{\mathbf{v}}_{k,i}^- | \mathbf{r}, \mathbf{H}\right)}, \quad i = 1, \ldots, 2^{K-1}. \tag{2}$$

In contrast to the Bayesian detector, our novel MUA SO ACO-MUD considers only the $\tilde{x}_k (\tilde{x}_k \ll 2^{K-1})$ number of combinations in both the search pool $\tilde{\mathbf{X}}_k^+$ and $\tilde{\mathbf{X}}_k^-$ used for calculating the LLR of the kth user. Hence, we have

$$L_k^{\mathrm{ACO}} = \ln \frac{\sum_{\tilde{\mathbf{x}}_{k,i}^+ \in \tilde{\mathbf{X}}_k^+} P\left(\tilde{\mathbf{x}}_{k,i}^+ | \mathbf{r}, \mathbf{H}\right)}{\sum_{\tilde{\mathbf{x}}_{k,i}^- \in \tilde{\mathbf{X}}_k^-} P\left(\tilde{\mathbf{x}}_{k,i}^- | \mathbf{r}, \mathbf{H}\right)}, \quad \begin{matrix} i = 1, \ldots, \tilde{x}_k, \\ \tilde{x}_k \ll 2^{K-1} \end{matrix}. \tag{3}$$

Exploiting Bayes' rule [8], we have $P(\mathbf{x}|\mathbf{r}, \mathbf{H}) = p(\mathbf{r}|\mathbf{x}, \mathbf{H})P(\mathbf{x})/p(\mathbf{r})$ and noting that the denominator of this formula may be expressed as $p(\mathbf{r}) = \sum_{i=1}^{2^K} p(\mathbf{r}|\mathbf{x}_i, \mathbf{H})P(\mathbf{x}_i)$, which is the same regardless which specific K-bit string $\mathbf{x}_i$ $i = 1, \ldots, 2^K$ is transmitted. Furthermore, noting that the *a priori* probabilities $P(\mathbf{x})$ are equal for all the 2^K legitimate transmit vectors at the commencement of the detection process, (2) and (3) can be further expressed as

$$L_k^{\mathrm{BAY}} = \ln \frac{\sum_{\tilde{\mathbf{v}}_{k,i}^+ \in \mathbf{V}_k^+} p\left(\mathbf{r}|\tilde{\mathbf{v}}_{k,i}^+, \mathbf{H}\right)}{\sum_{\tilde{\mathbf{v}}_{k,i}^- \in \mathbf{V}_k^-} p\left(\mathbf{r}|\tilde{\mathbf{v}}_{k,i}^-, \mathbf{H}\right)}, \quad i = 1, \ldots, 2^{K-1} \tag{4}$$

$$L_k^{\mathrm{ACO}} = \ln \frac{\sum_{\tilde{\mathbf{x}}_{k,i}^+ \in \tilde{\mathbf{X}}_k^+} p\left(\mathbf{r}|\tilde{\mathbf{x}}_{k,i}^+, \mathbf{H}\right)}{\sum_{\tilde{\mathbf{x}}_{k,i}^- \in \tilde{\mathbf{X}}_k^-} p\left(\mathbf{r}|\tilde{\mathbf{x}}_{k,i}^-, \mathbf{H}\right)}, \quad \begin{matrix} i = 1, \ldots, \tilde{x}_k, \\ \tilde{x}_k \ll 2^{K-1} \end{matrix}. \tag{5}$$

As shown in Section II, $\mathbf{r}$ is a random sample of the N_s-dimensional multivariate complex Gaussian distribution. Leaving out the mathematical derivations outlined in [7], the final form of L_k^{BAY} and L_k^{ACO} can be further expressed as

$$L_k^{\mathrm{BAY}} = \ln \frac{\sum\limits_{\tilde{\mathbf{v}}_{k,i}^+ \in \mathbf{V}_k^+} \exp\left\{\frac{-1}{2\sigma_n^2} \left\|\mathbf{r} - \mathbf{C}\mathbf{H}\tilde{\mathbf{v}}_{k,i}^+\right\|^2\right\}}{\sum\limits_{\tilde{\mathbf{v}}_{k,i}^- \in \mathbf{V}_k^-} \exp\left\{\frac{-1}{2\sigma_n^2} \left\|\mathbf{r} - \mathbf{C}\mathbf{H}\tilde{\mathbf{v}}_{k,i}^-\right\|^2\right\}} \quad i = 1 \ldots 2^{K-1} \tag{6}$$

$$L_k^{\mathrm{ACO}} = \ln \frac{\sum\limits_{\tilde{\mathbf{x}}_{k,i}^+ \in \tilde{\mathbf{X}}_k^+} \exp\left\{\frac{-1}{2\sigma_n^2} \left\|\mathbf{r} - \mathbf{C}\mathbf{H}\tilde{\mathbf{x}}_{k,i}^+\right\|^2\right\}}{\sum\limits_{\tilde{\mathbf{x}}_{k,i}^- \in \tilde{\mathbf{X}}_k^-} \exp\left\{\frac{-1}{2\sigma_n^2} \left\|\mathbf{r} - \mathbf{C}\mathbf{H}\tilde{\mathbf{x}}_{k,i}^-\right\|^2\right\}} \quad i = 1, \ldots, \tilde{x}_k, \quad \tilde{x}_k \ll 2^{K-1}. \tag{7}$$

2) Steps of the Algorithm: Before we detail the MUA SO-ACO algorithm, let us first formulate the likelihood value $Q(\mathbf{x})$ of a legitimate vector $\mathbf{x}$ during a certain symbol interval as

$$Q(\mathbf{x}) = 2\Re(\mathbf{x}^T\mathbf{y}) - \mathbf{x}^T\mathbf{R}\mathbf{x} \tag{8}$$

where we express the MF's output vector as $\mathbf{y} = (\mathbf{CH})^H\mathbf{r}$ and the correlation matrix of the composite CIR matrix given by the product of the CIR matrix $\mathbf{H}$ and signature matrix $\mathbf{C}$ during the current symbol interval as $\mathbf{R} = (\mathbf{CH})^H\mathbf{CH}$.

The objective of the algorithms is to create the search pool $\tilde{\mathbf{X}}_k^+$ and $\tilde{\mathbf{X}}_k^-$ having $\tilde{x}_k$ number of decision candidates in (7). To achieve this goal, we may firstly partition the entire search pool $\mathbf{X}$ of the original hard-output ACO-MUD into the two subsets of $\mathbf{X}_k^+$ and $\mathbf{X}_k^-$ based on the polarity of the kth bit of the vectors in $\mathbf{X}$. We denote the number of combinations in the subset $\mathbf{X}_k^{\pm}$ as $x_k^{\pm}$. However, we may find that we have $x_k^+ \neq x_k^-$ most of the time and that sometimes we may even have x_k^+ or $x_k^- = 0$, which results in either the numerator or the denominator of (7) becoming zero. This results in the corresponding LLR becoming $\pm\infty$, which in turn results in a potential error propagation in the channel decoding procedure. To avoid this situation, we will invoke two parallel search processes for each of the K users, during which the kth bit of all the vectors is fixed to $+1$ and -1, respectively. Thus, we may create the search pool $\mathbf{X}_k^+$ and $\mathbf{X}_k^-$ as the output of the corresponding two search processes, respectively.

Since we want $\tilde{\mathbf{X}}_k^{\pm}$ to contain the most dominant $\tilde{x}_k$ number of vectors from $\mathbf{X}_k^{\pm}$, we firstly sort all the elements in $\mathbf{X}_k^{\pm}$ in descending order according to their likelihood values, yielding their sorted counterparts $\overline{\mathbf{X}}_k^{\pm}$. We then denote the ith element in the subset $\overline{\mathbf{X}}_k^{\pm}$ as $\bar{\mathbf{x}}_{k,i}^{\pm}$. Thus, the most dominant vector in both sets is $\bar{\mathbf{x}}_{k,1}^{\pm}$. Furthermore, we denote the polarity Γ_k of the kth detected bit as the sign of the difference between the likelihood values of $\bar{\mathbf{x}}_{k,1}^{+}$ and $\bar{\mathbf{x}}_{k,1}^{-}$, i.e., we have $\Gamma_k = \text{sgn}\{Q(\bar{\mathbf{x}}_{k,1}^{+}) - Q(\bar{\mathbf{x}}_{k,1}^{-})\}$. Since the size of the search pool $\overline{\mathbf{X}}_k^{\pm}$ is only a small fraction of $\mathbf{V}_k^{\pm}$, most of the time we have $\bar{\mathbf{x}}_{k,i}^{\pm} \neq \bar{\mathbf{v}}_{k,i}^{\pm}$, given that the sorted counterpart of $\mathbf{V}_k^{\pm}$ is $\overline{\mathbf{V}}_k^{\pm}$. We may introduce an error, when we include the vector-pair $\bar{\mathbf{x}}_{k,i}^{\pm}$ in the calculation of L_k^{ACO}, if $Q(\bar{\mathbf{x}}_{k,i}^{+}) - Q(\bar{\mathbf{x}}_{k,i}^{-}) = -\Gamma_k$. To address this problem, we only incorporate the vector-pair $\bar{\mathbf{x}}_{k,i}^{\pm}$ into the calculation pool $\tilde{\mathbf{X}}_k^{+}$ and $\tilde{\mathbf{X}}_k^{-}$, respectively, if and only if $[Q(\bar{\mathbf{x}}_{k,i}^{+}) - Q(\bar{\mathbf{x}}_{k,i}^{-})] \cdot [Q(\bar{\mathbf{x}}_{k,1}^{+}) - Q(\bar{\mathbf{x}}_{k,1}^{-})] > 0$.

We may streamline the above descriptions in form of the following steps of the MUA SO-ACO algorithm used for generating the LLR L_k^{ACO} of the kth user.

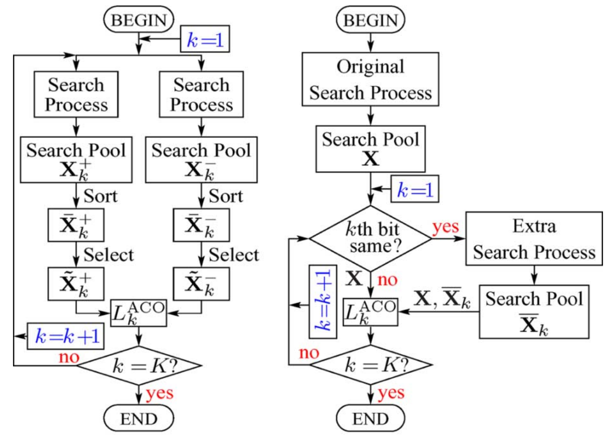
1)
   - Set the kth bit of all the vectors in the search pool $\mathbf{X}_k^{+}$ to $+1$.
   - Carry out a hard-decision-based ACO search, where the size of the route table[1] is reduced to $[(2 \times (K-1))]$ and record the value of the other $(K-1)$ bits of the x_k^{+} number of vectors in $\mathbf{X}_k^{+}$.
   - Sort the vectors in $\mathbf{X}_k^{+}$ according to their likelihood values as calculated in (8) and create the sorted pool $\bar{\mathbf{X}}_k^{+}$.
2)
   - Set the kth bit of all the vectors in the search pool $\mathbf{X}_k^{-}$ to -1.
   - Carry out a hard-decision-based ACO search, where the size of the route table[1] is reduced to $[(2 \times (K-1))]$ and record the value of the other $(K-1)$ bits of the x_k^{-} number of vectors in $\mathbf{X}_k^{-}$.
   - Sort the vectors in $\mathbf{X}_k^{-}$ according to their likelihood value as calculated in (8) and create the sorted pool $\bar{\mathbf{X}}_k^{-}$.
3) Compare the likelihood value of the two most dominant vectors $\bar{\mathbf{x}}_1^{\pm}$ in $\bar{\mathbf{X}}_k^{+}$ and $\bar{\mathbf{X}}_k^{-}$, respectively, and evaluate Γ_k as $\Gamma_k = \text{sgn}\{Q(\bar{\mathbf{x}}_{k,1}^{+}) - Q(\bar{\mathbf{x}}_{k,1}^{-})\}$.
4)
   a) Set $i = 2$
   b)

      if $(\text{sgn}\{Q(\bar{\mathbf{x}}_{k,i}^{+}) - Q(\bar{\mathbf{x}}_{k,i}^{-})\} = \Gamma_k \wedge i \leqslant \min\{x_k^{+}, x_k^{-}\})$
      - Push $\bar{\mathbf{x}}_{k,i}^{\pm}$ into $\tilde{\mathbf{X}}_k^{+}$ and $\tilde{\mathbf{X}}_k^{-}$, respectively.
      - $i = i + 1$ and go to Item 4)b.

      else Exit.
5) We let $\tilde{x}_k = i$, which is the number of vectors in the final search pool $\tilde{\mathbf{X}}_k^{+}$ and $\tilde{\mathbf{X}}_k^{-}$, respectively.
6) Get the LLR L_k^{ACO} according to (7).

The above algorithmic steps can be summarized in the flow chart of Fig. 2(a). Furthermore, the value of the parameter $\tilde{x}_k$ and $\tilde{\mathbf{X}}_k^{\pm}$ in (7) can be expressed as: $\tilde{x}_k = \arg\max_{1 \leqslant i \leqslant x_k}\{[Q(\bar{\mathbf{x}}_{k,i}^{+}) - Q(\bar{\mathbf{x}}_{k,i}^{-})][Q(\bar{\mathbf{x}}_{k,1}^{+}) - Q(\bar{\mathbf{x}}_{k,1}^{-})] > 0\}$ where $x_k = \min\{x_k^{+}, x_k^{-}\}$ and the search pool is given by: $\tilde{\mathbf{X}}_k^{\pm} = \{\tilde{\mathbf{x}}_{k,i}^{\pm} | \tilde{\mathbf{x}}_{k,i}^{\pm} = \bar{\mathbf{x}}_{k,i}^{\pm} \in \bar{\mathbf{X}}_k^{\pm}, 1 \leqslant i \leqslant \tilde{x}_k\}$.

[1]The terminology "route table" has been defined in more detail in [4].



(a) (b)

Fig. 2. Flow chart of the two SO ACO-based MUD algorithms. (a) MUA algorithm. (b) MAA algorithm.

TABLE I
ALL THE DIFFERENT VECTORS APPEARING DURING THE CURRENT SYMBOL INTERVAL ALONG WITH THEIR LIKELIHOOD VALUES

Trial vector $\mathbf{x}$	Likelihood $Q(\mathbf{x})$ of $\mathbf{x}$
$[+1\ \ -1\ \ +1\ \ +1\ \ \cdots\ \ -1]$	20.45
$\cdots$	$\cdots$

3) Complexity Issues: As the search procedure of the MUA algorithm progresses during a certain symbol interval, a large number of vectors will repeatedly appear in the search pools $\mathbf{X}_k^{\pm}$ of the search processes employed for evaluating the LLR value of different users k, $k = 1, \ldots, K$. For example, the same trial vector may appear in the search pool $\mathbf{X}_{k_1}^{+}, \mathbf{X}_{k_2}^{+}, \mathbf{X}_{k_3}^{-}$ when we have $k_1 \neq k_2 \neq k_3$. Thus, we may create a list containing all the different vectors appearing during the current symbol interval along with their likelihood values, as shown in Table I.

The likelihood value of a specific vector can be directly obtained from the table without further calculations, provided that it has already been calculated for this symbol interval. The same mechanism can be used to obtain the Euclidean distance associated with a specific vector, which is used in the calculation of L_k^{ACO}, as shown in (7). In conclusion, the complexity of the MUA algorithm is significantly reduced, as we will quantify in Fig. 4.

C. MAximum Approximation (MAA) SO ACO-MUD

The MAA Soft-ACO-based MUD algorithm has already been described in our previous work [7], which may be regarded as a special case of our novel MUA algorithm. More explicitly, the final form of the kth user's LLR in the MAA algorithm can still be described by (7). However, the value of the parameter $\tilde{x}_k$ and $\tilde{\mathbf{X}}_k^{\pm}$ in (7) will be simplified for the MAA algorithm as: $\tilde{x}_k = 1$ and $\tilde{\mathbf{X}}_k^{\pm} = \hat{\mathbf{x}}_k^{\pm}$, where we have $\hat{\mathbf{x}}_k^{+} = \bar{\mathbf{x}}_1^{+} = \arg\max\{Q(\mathbf{x}_{k,i}^{+})\}$ for all the $\mathbf{x}_{k,i}^{+} \in \mathbf{X}_k^{+}$ and $\hat{\mathbf{x}}_k^{-} = \bar{\mathbf{x}}_1^{-} = \arg\max\{Q(\mathbf{x}_{k,i}^{-})\}$ for all the $\mathbf{x}_{k,i}^{-} \in \mathbf{X}_k^{-}$. Moreover, the subsets $\mathbf{X}_k^{+}$ and $\mathbf{X}_k^{-}$ are obtained by partitioning the union $\mathbf{X} \cup \overline{\mathbf{X}}_k$ according to the polarity of the kth bit of every vector in the union set. Again, the flow chart of the MAA algorithm is detailed in Fig. 2(b).

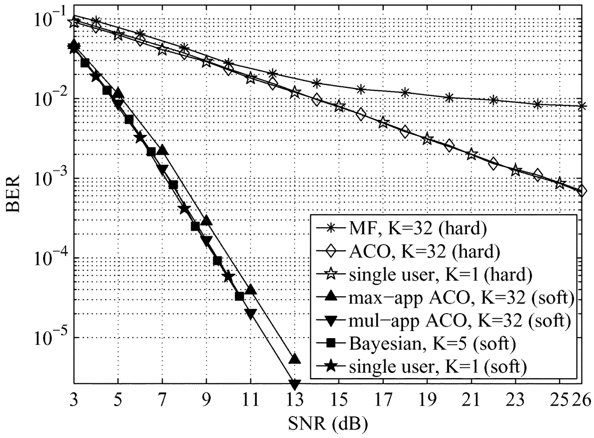


Fig. 3. BER versus SNR performance of the uplink DS-CDMA system for transmission over uncorrelated flat Rayleigh fading channels using $N_c = 31$-chip Gold codes.

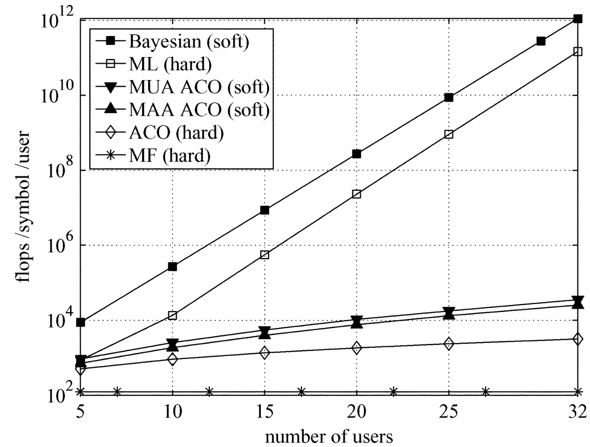


Fig. 4. Complexity per transmitted signal per user versus the number of users of the DS-CDMA system employing $N_c = 31$-chip Gold codes.

Let us now characterize the achievable performance of the SO ACO-based MUD.

IV. Simulation Results

The proposed SO ACO-based MUD was combined with a half-rate recursive systematic convolutional (RSC) code having a constraint length of 3 and employing the BCJR algorithm [11]. The octally represented generator and feedback polynominal of the RSC code was 7 and 5. The following parameters were used for the SO-ACO MUDs: initial pheromone $\tau = 0.01$, evaporation rate $\rho = 0.5$, number of ants $M = 10$, number of iterations $N = 10$, weight of pheromone $\alpha = 1$, weight of intrinsic affinity $\beta = 6$, and weight for the elite ant $\sigma = 8$. Additionally, the system employed a random interleaver length of 10^4 bits. Fig. 3 shows that the DS-CDMA UL supporting $K = 32$ users with the aid of $N_s = 31$-chip Gold codes is capable of approaching the corresponding single-user system's BER, regardless, whether the soft-output or hard-output ACO-based MUD is used. However, the soft-output ACO-assisted DS-CDMA scheme shows a significant SNR improvement compared to its hard-output ACO-assisted counterpart. We may also observe in Fig. 3 that the BER performance of both SO-ACO assisted DS-CDMA ULs supporting $K = 32$ users approaches that of its Bayesian assisted counterpart supporting $K = 5$ users. The Bayesian assisted DS-CDMA UL supports only $K = 5$ users because the complexity of the system supporting a higher number of users becomes excessive.

Fig. 4 shows that the complexity of the ACO-based MUD is only a fraction of that of the ML or Bayesian detector, again, regardless, whether hard- or soft-output aided detection is used. More quantatively, when the number of users reaches $K = 32$, the complexity of both the hard-output or the soft-output ACO is nearly a factor of 10^8 lower than that of the optimum Bayesian detector.

We observe a performance gap in Fig. 3 between the curve representing the MAA SO ACO-based MUD and the Bayesian MUD. This is because the MAA SO ACO-based MUD employs only the most dominant component in both the numerator and the denominator of the equation calculating the LLRs; thus, the LLR value is not as accurate as that obtained by the Bayesian MUD or by the MUA assisted SO ACO-based MUD. However, the BER performance of the MUA SO ACO-based MUD assisted DS-CDMA UL matches that of the Bayesian MUD, and it exhibits an obvious improvement compared to the MAA SO ACO-based MUD, while the complexity of the former is only slightly increased compared to that of the latter, as shown in Fig. 4.

V. Conclusion

In conclusion, the proposed MUA SO ACO-based MUD is capable of approaching the single-user performance, when combined with a 1/2-rate convolutional code, as seen for the DS-CDMA UL supporting $K = 32$ users when employing 31-chip Gold sequences. The complexity of the MUA SO ACO-based MUD is nearly a factor of 10^8 lower than that of the Bayesian MUD. The BER performance of the DS-CDMA UL employing the MUA assisted SO ACO-based MUD shows an improvement over the MAA assisted SO ACO-based MUD, while the complexity of the former is only slightly higher than that of the latter.

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