PAPER *Special Section on Spread Spectrum Techniques and Applications*

Multiuser Detection Using a Hopfield Network for Asynchronous Code-Division Multiple-Access Systems

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SUMMARY In this paper, a multiuser receiver using a Hopfield network (Hopfield network receiver) for asynchronous code-division multiple-access systems is proposed. We derive a novel likelihood function for the optimum demodulation of a data subsequence whose length is far shorter than that of the entire transmitted data sequence. It is shown that a novel Hopfield network receiver can be derived by exploiting the likelihood function, and the derived receiver leads to a low complexity receiver. The structure of the proposed receiver consists of a bank of correlators and a Hopfield network where the number of units is proportional to both the number of users and the length of a data sequence demodulated at a time. Computer simulation results are presented to compare the performance of the proposed receiver with those of the conventional multiuser detectors. It is shown that the proposed receiver significantly outperforms the correlation receiver, decorrelating detector and multistage detector, and provides suboptimum performance.

key words: *spread spectrum communications, near-far problem, multiple access interference, interference cancellation, neural networks*

1. Introduction

Recently, spread spectrum (SS) communication systems have been widely studied since their implementation became relatively easy. Especially, the SS communication systems are expected to be used in consumer communications whose share will increase [1]. SS systems have advantages such as anti-multipath fading capability and anti-jamming capability. Moreover, realization of code-division multiple-access (CDMA) is one of advantages of the SS systems.

CDMA has recently received considerable attention as an alternative to frequency-division multiple-access (FDMA) in wireless communications. CDMA is expected to have a larger capacity than FDMA because of the following two advantages [2]. First, the bursty nature of a source can be exploited effectively so that it is essentially suited for statistical multiplex. Second, the frequency reuse factor can be one. In direct-sequence (DS)/CDMA systems employing the correlators (matched filters), the major drawback is the near-far problem, i.e., performance degradation due to the multiple-access interference (MAI). Thus, cancellation of the MAI is necessary to increase capacity.

Several techniques to cancel the MAI have been proposed [3]–[19]. The complexity of the optimum multiuser detection [3], [4] based on the maximum likelihood sequence detection grows exponentially with increasing the number of users. Therefore, a suboptimum receiver which is robust to the near-far problem with low complexity is required. Two types of the receiver whose complexity is proportional to the number of users have been mainly considered. One is the decorrelating detector [5], [6] and the other is the multistage detector [7], [8]. The decorrelating detector is a linear system and it can not provide sufficient performance. Because it is known that nonlinear structure is needed to perform the optimum detection because of the nonlinearity of the optimum decision boundary [9]. On the other hand, although the multistage detector is a nonlinear system, its performance degrades unless received amplitude for each user extremely differs. Other examples of suboptimum detectors can be found in [10].

In this paper, a multiuser detection employing a neural network in an asynchronous CDMA channel is considered. Neural networks provide high computational rates because a large number of simple nonlinear processing units operate in parallel [20]. Two well-known neural networks are the multilayer neural network and the recurrent neural network.

Aazhang et al. [9] proposed a multiuser receiver using the multilayer neural network trained by the back propagation algorithm and Mitra et al. [11] proposed a multiuser receiver using a radial basis function network which is a kind of the multilayer neural network. Although these receivers provide suboptimum performance, the number of units needed grows exponentially with increasing the number of users. Thus, these multilayer neural network receivers provide few gain in terms of simplicity.

The Hopfield network is a kind of the recurrent neural networks and has a potentiality to solve optimization problems [21]. The Hopfield network has been successfully applied to many optimization problems in communication systems [22], e.g., decoding of error correcting codes [23] and maximum-likelihood sequence estimation [24].

The optimum multiuser detection for CDMA systems can also be viewed as an optimization problem,

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since it results in finding the most likely information bits which maximize a likelihood function. There have been attempts for the multiuser receiver using Hopfield networks (referred to as Hopfield network receiver) [12]–[17]. Early studies have been made on synchronous CDMA systems [12]–[14]. These exploit the well-known likelihood function by Lupas et al. [18]. Miyajima et al. [12] and Kechriotis et al. [13] examined the BPSK signal case independently, and Nagaosa et al. [14] examined the M-ary signal case.

In most practical CDMA systems, however, the transmitters send information independently, so that signals from different users arrive asynchronously at the receiver. Therefore, it is important to design receivers suited for the asynchronous CDMA systems. Miyajima et al. [15] and Kechriotis et al. [16] proposed the Hopfield network receiver for an asynchronous CDMA system independently. These exploit well-known Verdú's likelihood function which is related to the optimum entire sequence demodulation [4]. Consequently, the resulting Hopfield network receiver demodulates the entire transmitted data sequence at a time. Its complexity is proportional to both the number of the users and the length of a data sequence demodulated at a time. In general, however, since the length of the entire transmitted data sequence becomes long, the Hopfield network receiver becomes too complex to implement. Thus, the methodology [12] which exploits a well-known likelihood function may not be useful for asynchronous CDMA systems. An alternative likelihood function to Verdú's function is required to design a low complexity Hopfield network receiver.

The purpose of this paper is to consider a low complexity Hopfield network receiver for asynchronous CDMA systems†. As mentioned above, the complexity of Hopfield network receivers is closely related to the length of a data sequence demodulated at a time. The main contribution of this paper is to derive a novel likelihood function for the optimum demodulation of a data subsequence whose length is far shorter than that of the entire data sequence. It will be shown that a novel Hopfield network receiver can be derived by exploiting the likelihood function, and the derived receiver leads to a low complexity receiver.

The rest of this paper is organized as follows. An asynchronous CDMA communication model and the optimum multiuser detection for a data subsequence are described in Sect. 2. In Sect. 3, the Hopfield network is explained and the receiver employing the Hopfield network is presented. Section 4 gives computer simulation results to compare its performance with those of the correlation, optimum, decorrelating and multistage detector. Finally, in Sect. 5, we summarize the main results.

2. Communication Model and Optimum Multiuser Detection

Let us assume that there are K transmitters in the system, and each transmitter employs a BPSK DS/SS signal.

The received signal can be written as

$$r(t) = S(t) + n(t) \tag{1}$$

where $n(t)$ is white Gaussian noise with two-sided power spectral density $N_0/2$ and

$$S(t) = \sum_{p=-\infty}^{\infty} \sum_{k=1}^{K} b_k^{(p)} s_k(t - pT_b - \tau_k) \tag{2}$$

where $b_k^{(p)} \in \{-1, 1\}$ is the pth transmitted bit of the kth user, T_b is the bit interval duration and $\tau_k \in [0, T_b)$ are the time delay of the kth user. Without loss of generality, we suppose that the users are numbered such that $0 \leqq \tau_1 \leqq \cdots \leqq \tau_K < T_b$. The signature waveform of the kth user is time-limited to $[0, T_b]$ and given as

$$s_k(t) = A_k a_k(t) \cos(\omega_c t + \theta_k) \tag{3}$$

where A_k is the kth user's signal amplitude, ω_c is the common carrier frequency, θ_k is the phase angle of the kth user. The signal energy per bit of the kth user is denoted by E_k. The spreading signal which is a time limited signal can be written in the form

$$a_k(t) = \sum_{i=0}^{L-1} a_i^{(k)} p_{T_c}(t - iT_c) \tag{4}$$

where $p_{T_c}(t)$ is the unit rectangular pulse of duration T_c, i.e., $p_{T_c}(t) = 1$ for $0 \leqq t < T_c$ and $p_{T_c}(t) = 0$ otherwise, T_c is the chip duration, and $\{a_i^{(k)} \in \{-1, 1\}\}$ is the spreading sequence whose length is $L = T_b/T_c$.

In the following, the amplitudes and time delays of all the users are assumed to be known. Moreover, the channel is assumed to be time invariant. Although, in general, the received signal is converted to I, Q components at baseband, only the I component is used by assuming the carrier phase be known in this paper.

Consider the optimum multiuser demodulation for PK bits which include data from the ith bit to the $i+P-1$st bit of all the K users, where P is the length of the data sequence demodulated at a time. Note that we investigate the optimum multiuser demodulation for the data subsequence consisting of PK bits, not that for the entire transmitted data sequence [4], [15], [16]. The reason to consider the optimum data subsequence demodulation is to derive a corresponding suboptimum receiver which has low complexity. Its complexity can be limited by P as described in Sect. 3.

†The first Hopfield network receiver for asynchronous CDMA systems was proposed by the present authors. The basic idea of this paper was presented in [17].

Since the noise is white and Gaussian and all transmitted data sequences are assumed to be equiprobable, the maximum-likelihood sequence detector selects the data sequence $\{\widehat{\boldsymbol{b}}^{(p)} = [\widehat{b}_1^{(p)}, \cdots, \widehat{b}_K^{(p)}]^T, p = i-1, \cdots, i+P\}$ that minimizes

$$\int_{iT_b+\tau_1}^{(i+P)T_b+\tau_K} \left[r(t) - \widehat{S}(t)\right]^2 dt \tag{5}$$

where

$$\widehat{S}(t) = \sum_{p=-\infty}^{\infty} \sum_{k=1}^{K} \widehat{b}_k^{(p)} s_k(t - pT_b - \tau_k). \tag{6}$$

The minimization of (5) is equivalent to the maximization of the following likelihood function

$$\begin{aligned} L = {} & \widehat{\boldsymbol{b}}^{(i-1)T}\{2\boldsymbol{y}'^{(i-1)} - \boldsymbol{H}'\widehat{\boldsymbol{b}}^{(i-1)}\} \\ & + \sum_{p=i}^{i+P-1} \widehat{\boldsymbol{b}}^{(p)T}\{2\boldsymbol{y}^{(p)} - \boldsymbol{H}(0)\widehat{\boldsymbol{b}}^{(p)} - 2\boldsymbol{H}(1)\widehat{\boldsymbol{b}}^{(p-1)}\} \\ & + \widehat{\boldsymbol{b}}^{(i+P)T}\{2\boldsymbol{y}''^{(i+P)} - \boldsymbol{H}''\widehat{\boldsymbol{b}}^{(i+P)} \\ & \qquad - 2\boldsymbol{H}(1)\widehat{\boldsymbol{b}}^{(i+P-1)}\} \end{aligned} \tag{7}$$

where $\boldsymbol{y}'^{(i-1)}, \boldsymbol{y}^{(p)}, \boldsymbol{y}''^{(i+P)}$ are the $K \times 1$ correlator output vectors and their kth elements are given as

$$y_k'^{(i-1)} = \int_{iT_b+\tau_1}^{iT_b+\tau_k} s_k(t - (i-1)T_b - \tau_k) r(t) dt, \tag{8a}$$

$$y_k^{(p)} = \int_{pT_b+\tau_k}^{(p+1)T_b+\tau_k} s_k(t - pT_b - \tau_k) r(t) dt, \tag{8b}$$

$$y_k''^{(i+P)} = \int_{(i+P)T_b+\tau_k}^{(i+P)T_b+\tau_K} s_k(t - (i+P)T_b - \tau_k) r(t) dt, \tag{8c}$$

and $\boldsymbol{H}', \boldsymbol{H}(i), \boldsymbol{H}''$ are the $K \times K$ cross-correlation matrices and their (k,l)th elements can be written as

$$h'_{kl} = \int_{\tau_1}^{\tau_k} s_k(t + T_b - \tau_k) s_l(t + T_b - \tau_l) dt, \tag{9a}$$

$$h_{kl}(i) = \int_{\tau_k}^{T_b+\tau_k} s_k(t - \tau_k) s_l(t + iT_b - \tau_l) dt, \tag{9b}$$

$$h''_{kl} = \int_{\tau_k}^{\tau_K} s_k(t - \tau_k) s_l(t - \tau_l) dt \tag{9c}$$

since $s_k(t)$ is the time-limited signal. The relation among the information bits, correlator outputs of each user and cross-correlations is illustrated in Fig. 1. In this figure, the cross-correlations between the first user and the Kth user are omitted for ease of understanding. Consequently, the optimum receiver can be implemented by a bank of K correlators followed by the Viterbi algorithm with 2^{K-1} states. The complexity of the receiver grows exponentially with increasing the number of users K, and is thus impractical for a large number of users.

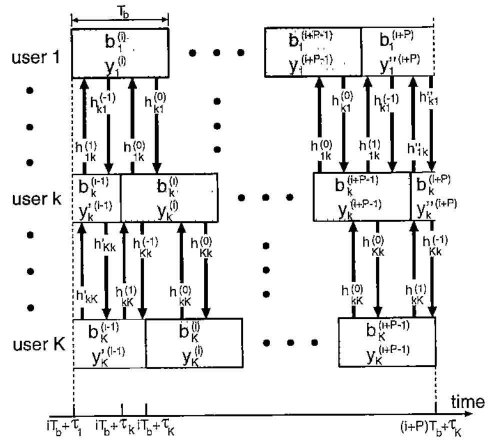

Fig. 1 Relation among information bits, correlator outputs and cross-correlations.

3. Multiuser Detection Using a Hopfield Network

3.1 Hopfield Network

The Hopfield network consists of a number of simple nonlinear units. The equation of motion describing the time evolution of the network is

$$\frac{du_i}{dt} = -\frac{u_i}{\tau} + \sum_{j=1}^{M} T_{ij} V_j + I_i \tag{10}$$

$$V_i = \tanh(\lambda u_i) \tag{11}$$

where u_i and V_i are the potential and output of the ith unit respectively, T_{ij} is the connection weight from the jth unit to ith one, I_i is the external input to the ith unit, M is the number of the units in the network, τ is the time constant and λ is a gain scaling parameter which changes the steepness of the sigmoid gain curve. The vector

$$\boldsymbol{V} = [V_1, \cdots, V_M]^T \tag{12}$$

is regarded as a state of the network. Given an initial state, the state changes according to (10) and (11).

Hopfield showed [25] that if connection weights are symmetric, i.e., $T_{ij} = T_{ji}$, the state of the network always converges to a stable state. When the self-connections are 0, i.e., $T_{ii} = 0$ and the width of the transition region of the sigmoid gain curve is narrow, corresponding to high gain, the stable states of the network are the local minima of the quantity

$$E = -\sum_{i=1}^{M} V_i I_i - \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M} T_{ij} V_i V_j. \tag{13}$$

The function E is called the energy function. In the high-gain limit network with vanishing self-connections, the minima occur only at the corners of an M-dimensional hypercube defined by $V_i = +1$ or -1.

Hopfield networks can be implemented by a simple analog electrical circuit [25] or analog LSI [26]. Analog, digital or hybrid VLSI implementation of neural networks including Hopfield networks can be found in Chapter 15 of [20].

3.2 Hopfield Network Receiver

Consider a receiver using the Hopfield network where the output of each unit corresponds to the estimation for the information bit of each user in each time interval. It is desirable to demodulate an entire transmitted data sequence optimally as in the case of the synchronous CDMA system [12]. However, since each bit overlaps with several bits for the asynchronous CDMA system, the likelihood function for an entire data sequence is defined over an entire data sequence [4]. In general, an entire data sequence is over a long period. Consequently, the corresponding Hopfield network receiver [15], [16] has high complexity, i.e., a large number of units are required, so that it is not reallistic to implement the receiver. Thus, we have considered the optimum demodulation for a data subsequence consisting of PK bits in Sect. 2. Here, we derive the corresponding Hopfield network receiver whose complexity can be limited by P. It is noted that the proposed receiver is nearly equal to the Hopfield network receiver for the entire data sequence demodulation when P is sufficiently large.

It is clear from (7) that the number of units results in $M = (P+2)K$ for the demodulation of PK bits. The network can be divided into $P+2$ subnetworks. Each subnetwork consists of K units. Then, the kth unit in the pth subnetwork corresponds to the pth bit of the kth user. The output of the kth unit in the pth subnetwork is computed by

$$\frac{du_k^{(p)}}{dt} = -\frac{u_k^{(p)}}{\tau} + \sum_{q=0}^{P+1}\sum_{l=1}^{K} T_{k\ l}^{(p)(q)} V_l^{(q)} + I_k^{(p)} \tag{14}$$

$$V_k^{(p)} = \tanh(\lambda u_k^{(p)}) \tag{15}$$

where $u_k^{(p)}, V_k^{(p)}$ and $I_k^{(p)}$ are the potential, output and external input of the kth unit in the pth subnetwork respectively, and $T_{k\ l}^{(p)(q)}$ is the connection weight from the lth unit in the qth subnetwork to the kth unit in the pth subnetwork. The energy function of the network using vector notation is defined by

$$E = -\sum_{p=0}^{P+1} \boldsymbol{V}^{(p)T}\boldsymbol{I}^{(p)} - \frac{1}{2}\sum_{p=0}^{P+1}\sum_{q=0}^{P+1} \boldsymbol{V}^{(p)T}\boldsymbol{T}^{(p)(q)}\boldsymbol{V}^{(q)} \tag{16}$$

where $\boldsymbol{V}^{(p)}$ is the $K \times 1$ unit output vector of the pth subnetwork whose kth element is $V_k^{(p)}$, $\boldsymbol{I}^{(p)}$ is the $K \times 1$ external input vector of the pth subnetwork whose kth element is $I_k^{(p)}$, and $\boldsymbol{T}^{(p)(q)}$ is the $K \times K$ connection weight matrix from the qth subnetwork to the pth one whose (k,l)th element is $T_{k\ l}^{(p)(q)}$.

Each parameters of the Hopfield network are determined by comparing the likelihood function (7) and the energy function (16). The resulting parameters are given by

$$\boldsymbol{I}^{(p)} = \begin{cases} 2\boldsymbol{y}'^{(i-1)} & p = 0 \\ 2\boldsymbol{y}^{(i+p-1)} & 1 \leqq p \leqq P \\ 2\boldsymbol{y}''^{(i+P)} & p = P+1 \end{cases} \tag{17}$$

$$\boldsymbol{T}^{(p)(q)} = \begin{cases} -2\boldsymbol{H}' & p = q = 0 \\ -2\boldsymbol{H}(0) & p = q \text{ and } 1 \leqq p \leqq P \\ -2\boldsymbol{H}'' & p = q = P+1 \\ -2\boldsymbol{H}(1) & p = q+1 \\ -2\boldsymbol{H}(-1) & p = q-1 \\ \mathbf{o} & \text{otherwise} \end{cases} \tag{18}$$

It is obvious from (9) that $h'_{kl} = h'_{lk}, h''_{kl} = h''_{lk}$ and $h_{kl}(i) = h_{lk}(-i)$, i.e., the connection weights are symmetric. Thus, the energy function always decreases as the state changes. On the other hand, the diagonal elements of the cross-correlation matrices are nonzero. Since the data sequence which maximizes the likelihood function corresponds to a corner of the hypercube, one should consider the energy at each corner. The contribution of the self-connections to the energy function is given by $\sum_{p=0}^{P+1}\sum_{k=1}^{K} V_k^{(p)2} T_{k\ k}^{(p)(p)}$ and is constant at a corner of the hypercube. Therefore the relations between the energies at all the corners can be maintained even if the self-connections vanish. Moreover, as mentioned above, in the high-gain limit network with vanishing self-connections the state of the network always converges to one of corners of the hypercube and it does not converge to interior of the hypercube. Thus, setting the self-connections zero does not affect searching of the state which minimizes the energy function. Consequently, the Hopfield network whose parameters are determined by (17), (18) with zero self-connections can be used to search the data sequence which maximizes the likelihood function.

It should be noted that the optimum detection can be achieved only when the state of the network converges to the global minimum of the energy function. However, it is only ensured that the state converges to one of minima. If the state converges to a local minimum except the global minimum, the performance of the Hopfield network receiver degrades. However, even if the state converges to a local minimum, the local minimum can be expected to be roughly the same as the global one as in the case of the traveling salesman problem [21]. Hence, the decision obtained by the Hopfield network receiver is expected to be the suboptimum decision.

Figure 2 shows the structure of the resulting Hopfield network receiver. There are the K correlators which is concerned with each user. The correlator outputs $\{y_k'^{(i-1)}, k = 1, \cdots, K\}, \{y_k^{(p)}, k = 1, \cdots, K; p = i, \cdots, i+P-1\}, \{y_k''^{(i+P)}, k = 1, \cdots, K\}$ are stored in the memory to demodulate PK bits from the ith to $i+P-1$st bit for all the K users and then these are input to the Hopfield network. The Hopfield network changes its state according to (14) and (15) until the state converges. After the convergence, the estimation for the bit of each user in each time interval, denoted by $\tilde{b}_k^{(i+p-1)}$ can be obtained by hard-limiting the output of each unit.

$$\tilde{b}_k^{(i+p-1)} = \mathrm{sgn}(V_k^{(p)}). \tag{19}$$

Connections of the network are illustrated in Fig. 3. The network consists of $P+2$ subnetworks which consist of K units and the units in a subnetwork is connected to the units in the same subnetwork and the units in the adjoining subnetworks. This is caused by the fact that the MAI results from transmitted signals of other users in the same time interval and the adjoining time intervals. Note that the hardware complexity of the proposed receiver is proportional to both the number of users, K, and the length of a data sequence demodulated at a time, P, since the number of units which are modeled as amplifiers is $(P+2)K$.

Although the Hopfield network receiver demodulates $(P+2)K$ bits from $i-1$st bit to $i+P$th bit for all the K users, the decisions for the $i-1$st bit and $i+P$th bit are neglected. Because sufficient statistics for the $i-1$st and $i+P$th bit can not be obtained.

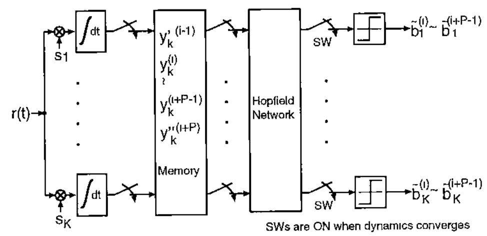

Fig. 2 Receiver structure.

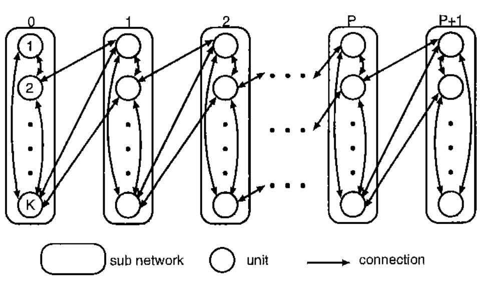

Fig. 3 Connections between units.

4. Simulation Results

Performance comparisons among the optimum receiver described in Sect. 2, correlation receiver, decorrelator by Kohno et al. [5], multistage detector by Varanasi et al. [8] and proposed Hopfield network receiver were carried out via computer simulation.

As for the Hopfield network receiver, two different criteria were used to determine when to stop a particular simulation. The first of these was the convergence criterion. After each update, the squares of the differences between the new output values and the old ones were computed. If no value had changed by more than 10^{-8}, the network was considered to be converged. The second was the time limit criterion. The computations were stopped after the simulation of 10τ seconds (10 time constants). The initial values of the unit outputs are set to zero [27]. The gain scaling parameter in (15) was set to $\lambda = 50$ which provided good results for the traveling salesman problem [21]. Effects of λ was discussed for a synchronous noiseless scenario in [19]. The number of stages was five for the multistage detector and the length of the data sequence detected at a time was ten for the decorrelator. The bit error rates were averaged over ten random time delays τ_k. We used a baseband system to reduce the required computation. Since the bit error rate for the 1st user was considered, it was assumed that the signals of the users except the 1st user had equal energy per bit which was denoted by E_i.

Firstly, it was assumed that there are five users in a channel where the spreading codes employed were Gold sequences of length 7. Now, we consider the length of the data sequence demodulated at a time P. The bit error rate versus P is shown in Fig. 4. In this figure, the energy of the 1st user's signal to the power spectral den-

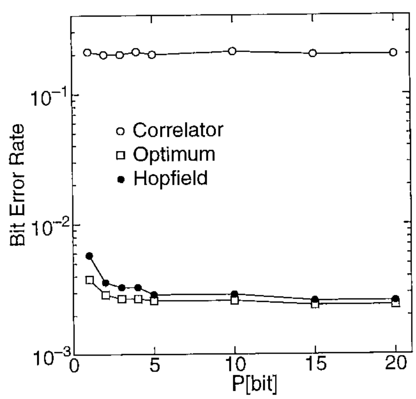

Fig. 4 Bit error rate versus length of data sequence demodulated at a time ($E_1/N_0 = 6$ dB, $E_i/E_1 = 5$ dB, $K = 5$, $L = 7$).

sity of noise ratio E_1/N_0 is fixed at 6 dB and the signal energy of the interfering user to that of the 1st user ratio E_i/E_1 is fixed at 5 dB. The performance of the correlator remains invariant with the length of the data sequence. Since the performances of the decorrelator and multistage detector are also invariant with the data sequence length, these are omitted from the figure. The Hopfield network receiver can achieve the suboptimum performance regardless of the data sequence length. Since the bit error rate converges to a certain value at larger than $P = 5$, we chose $P = 10$ in the following simulation. In cases of the data sequence length less than five, the performance of the Hopfield network receiver degrades. As described in Sect. 3, available statistics to demodulate the edge bits are insufficient. Because of this edge effect, the performance degrades in cases of the short length. The edge effect can be mitigated by setting the data sequence length long or overlapping. It is noted, however, that lengthening the length of the data sequence demodulated at a time and overlapping several bits between adjacent intervals may provide better results, but grow complexity and lead to long decoding delay.

Next, we consider the convergence property of the Hopfield network receiver. As an example, results for changing E_i/E_1 in the five user channel are shown. Figure 5 shows the rate of convergence within 10τ seconds as a function of E_i/E_1 where $E_1/N_0 = 6$ dB. One can observe that most simulations are terminated within 10τ seconds. The mean time needed to converge versus E_i/E_1 is illustrated in Fig. 6 where $E_1/N_0 = 6$ dB. These results indicate that 10τ seconds is sufficient for the time limit criteria in the simulation presented here. Time needed to converge may vary in communication scenarios. Provided that sufficient long time period is available, the time limit criteria should be as long as possible.

Next, the bit error rate performance was considered in the five user channel. In Fig. 7, the bit error rate of the 1st user versus E_1/N_0 where E_i/E_1 is fixed at 5 dB is depicted. The bit error rate performance of the Hopfield network receiver is better than those of the decorrelator and multistage detector, and it is nearly equal to that of the optimum detector over the range of E_1/N_0.

Next, the near-far capability was considered in the five user channel. Figure 8 depicts the bit error rate of the 1st user as a function of E_i/E_1 where E_1/N_0 is fixed at 6 dB. One can observe that the Hopfield network re-

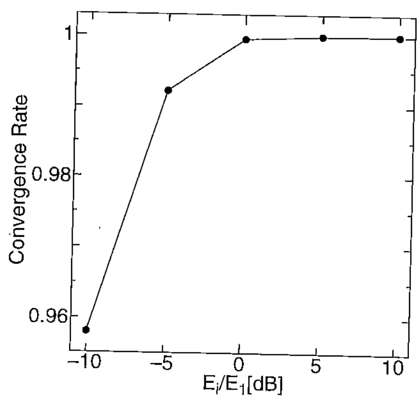

Fig. 5 Convergence rate within 10τ versus E_i/E_1 ($E_1/N_0 = 6$ dB, $P = 10$, $K = 5$, $L = 7$).

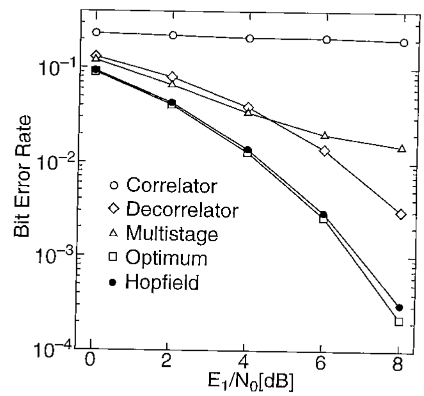

Fig. 7 Bit error rate versus E_1/N_0 ($E_i/E_1 = 5$ dB, $P = 10$, $K = 5$, $L = 7$).

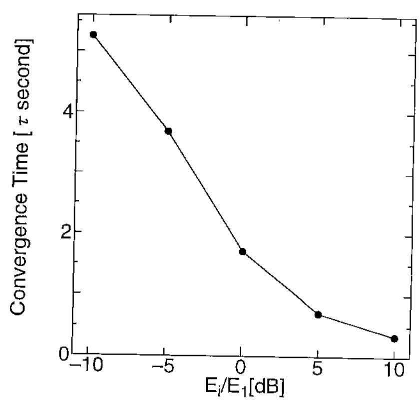

Fig. 6 Time needed to converge versus E_i/E_1 ($E_1/N_0 = 6$ dB, $P = 10$, $K = 5$, $L = 7$).

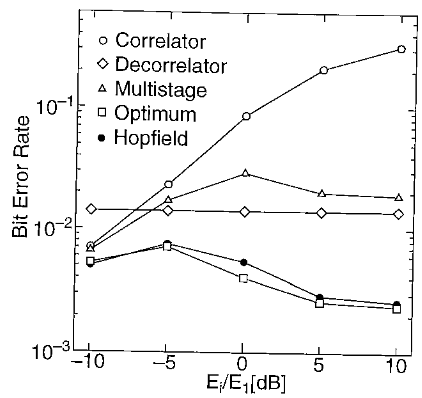

Fig. 8 Bit error rate versus E_i/E_1 ($E_1/N_0 = 6$ dB, $P = 10$, $K = 5$, $L = 7$).

ceiver outperforms both the decorrelator and multistage detector over the range of E_i/E_1 and its performance is suboptimum.

It can be seen from Fig. 8 that the worst performance point is near $E_i/E_1 = -5$ dB. The Hopfield network receiver cancels the MAI by estimating and subtracting it. If E_i/E_1 is sufficiently small, performance degradation due to the MAI is small. If E_i/E_1 is sufficiently large, the MAI estimation is relatively easy since the interference component is large. On the contrary, it is hard to estimate the MAI at intermediate points, i.e., points near -5 dB in Fig. 8, since the MAI is buried in channel noise. It can be considered that the worst point is determined by both magnitudes of the MAI and channel noise. Therefore, the parameters which are related to these magnitudes, such as E_1/N_0, K and spreading sequences, may affect the worst performance point, but sufficiently large P may not.

It is important to consider the situation where no user exists except the 1st user. In asynchronous communication systems, in general, the situation where E_i/E_1 is very small can be occurred. Since no user exists except the 1st user, the signature waveforms $s_k(t)$ are zero for $k = 2, \cdots, K$. Therefore, the cross-correlations $h_{kl}(i), h'_{kl}$ and h''_{kl} are zero for $k \neq l$, and the correlator outputs $y_k^{(p)}, y_k'^{(i-1)}$ and $y_k''^{(i+P)}$ are also zero for $k = 2, \cdots, K$. Considering the self connections $T_{k\ k}^{(p)(p)}$ are zero, then we get

$$E = -2V_1^{(0)} y_1'^{(i-1)} - \sum_{p=1}^{P} 2V_1^{(p)} y_1^{(i+p-1)} - V_1^{(P+1)} y_1''^{(i+P)}. \tag{20}$$

Since the resulting energy function is linear for each unit's output, the network is guaranteed to find the optimum solution. Then the optimum solution corresponds to the decision of the correlation receiver since the correlation receiver can achieve the optimum demodulation in the Gaussian channel without MAI.

Consider now the number of available users. The spreading codes employed were Gold sequences of length 31 to examine the larger number of users case. Figure 9 shows the bit error rate versus the number of users ranging from $K = 10$ to 30 when E_1/N_0 is 6 dB and E_i/E_1 is 0 or 5 dB. We chose $P = 10$ which provides a good result as shown in Fig. 9. In this case, we could not compute the bit error rate for the optimum receiver because it requires enormous computational load. When the number of users increases, the performance degradation of the Hopfield network receiver is little in relation to the conventional suboptimum receivers. Moreover, one can see that the performance of the correlation receiver becomes worse and that of the Hopfield network receiver becomes better as the signal energies of interfering users become stronger.

Lastly, it may be worth mentioning the relation between the Hopfield network receiver and multistage detector [8]. The methods of the MAI cancellation for both the Hopfield network receiver and the multistage detector are based on estimation and subtraction of the MAI. As pointed out by Kechriotis et al. [19] the Hopfield network receiver is identical to the multistage detector under certain conditions. In fact, the multistage detector can be regarded as a classical neural network used for the associative memory [20]. The reason why the Hopfield network receiver outperforms the multistage detector can be found in [19].

5. Conclusions

In this paper, we have proposed the multiuser detector using a Hopfield network in asynchronous code-division multiple-access communications and compared its performance with conventional multiuser detectors via computer simulation. It has been shown that a low complexity Hopfield network receiver can be designed by investigating the optimum multiuser detection for a data subsequence with short length. The number of units in the Hopfield network is proportional to both the number of users and the length of a data sequence demodulated at a time. Simulation results have shown that the Hopfield network receiver can achieve suboptimum performance and outperforms the correlation, decorrelating and multistage detector. The length of the spreading codes used may be short and the number of the users may also be small in our simulation. This is due to reduce the computational load. However, since the ratio of the number of the users to the processing gain is high, i.e., 5/7 and 30/31, the results would provide useful data for designing more practical systems.

The Hopfield network receiver, like the optimum receiver, requires knowledge of the signal amplitudes, spreading sequences, time delays and carrier phases for all the users. These parameters must be estimated and

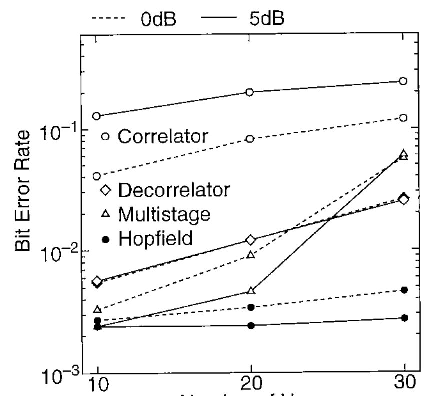

Fig. 9 Bit error rate versus number of users ($E_1/N_0 = 6$ dB, $E_i/E_1 = 0$ dB and 5 dB, $P = 10$, $L = 31$).

updated in time varying channels. A parameter estimation algorithm developed for the conventional receiver [28] may be available for the Hopfield network receiver. Further studies for both the parameter estimation and effects of estimation error are necessary.

There have been increasing interests for adaptive receivers [10]. Recently, an adaptive version of the Hopfield network receiver for a synchronous DS/CDMA system has been proposed [29]. In contrast to the proposed receiver, the adaptive receiver has no knowledge about both the signal amplitudes and spreading sequences for all the users, but estimates these by RLS algorithm with the training signal. Although it was shown that the receiver provides good performance for a simple example [29], further consideration for more practical situations is needed. Moreover, the adaptive Hopfield network receiver for an asynchronous DS/CDMA system has to be developed.

Since the performance analysis is very hard owing to the nonlinearity, the performance of the Hopfield network receiver has been evaluated by computer simulation in this paper. Theoretical analysis of the Hopfield network receiver is our future work. The Hopfield network receiver may be implemented by employing a neuro-chip which is being rapidly developed. Hardware implementation of the receiver is the subject for a future study.

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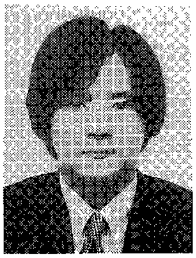

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