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An Adaptive Multiuser Receiver Using a Hopfield Network

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SUMMARY In this letter, we propose an adaptive multiuser receiver using a Hopfield network for code-division multiple-access communications and its performance is compared with that of the other types of multiuser receiver via computer simulation. The proposed adaptive receiver estimates both the signal amplitudes and spreading sequences for all the users using training data.

key words: *multiuser receiver, adaptive receiver, Hopfield network, code-division multiple-access, near-far problem*

1. Introduction

In code-division multiple-access communications, several users simultaneously transmit information over a common channel. It is known that when the relative power of the multiple-access interference is large, i.e., the near-far problem, the performance of the conventional matched filter receiver degrades. On the other hand, the complexity of the optimum multiuser receiver grows exponentially with increasing the number of users [1]. Thus, suboptimum receivers whose complexity is proportional to the number of users have been proposed [1]–[6]. We proposed a multiuser receiver using a Hopfield network (referred to as "Hopfield network receiver") and showed that the receiver has simple structure and near-optimum performance [2], [3]. The Hopfield network receiver requires both the received signal amplitudes and the spreading sequences of all the users. However, these parameters are not always known in practical communication environment. In cases these parameters are unknown and/or time variant, adaptive systems are useful to estimate and/or track these parameters [4]–[6]. In this letter, we propose an adaptive multiuser receiver using a Hopfield network. The proposed receiver estimates both the signal amplitudes and spreading sequences for all the users using training data.

2. Adaptive Hopfield Network Receiver

We consider a synchronous direct-sequence code-division multiple-access (DS/CDMA) communication system. The baseband received signal is expressed as

$$r(t)=\sum_{k=1}^{K}\sum_{l=1}^{L}A_k a_{kl} P_{T_c}[t-(l-1)T_c]b_k(t)+n(t) \quad (1)$$

here K is the number of users, L is the length of the spreading sequences, A_k is the signal amplitude of the kth user, $a_{kl} \in \{+1,-1\}$ is the lth chip of the kth user's spreading sequence, $b_k(t)$ is the information bit of the kth user and $P_{T_c}[t]$ is the rectangler pulse of the chip duration T_c.

In the Hopfield network receiver, its external inputs, I_i, and connection weights, T_{ij}, are determined by [2]

$$I_i = 2\int_0^{T_b} r(t)s_i(t)dt, \quad (2)$$

$$T_{ij} = -2\int_0^{T_b} s_i(t)s_j(t)dt \quad (3)$$

where

$$s_i(t) = A_i \sum_{l=1}^{L} a_{il} P_{T_c}[t-(l-1)T_c] \quad (4)$$

and T_b is the bit duration. We showed that a maximum point of the likelihood function of the optimum multiuser detection [1] can be searched by dynamics of the Hopfield network and the bit error rate achieved by the Hopfield network receiver is near-optimum [2], [3]. The Hopfield network receiver requires the signal amplitudes, $\{A_i\}$, and spreading sequences, $\{a_{il}\}$, of all the users. We propose a system to estimate both the amplitudes and spreading sequences simultaneously using a chip matched filter, RLS algorithm [7] and training data.

It is assumed that a receiver has no knowledge about both the signal amplitudes and spreading sequences. The output of the chip matched filter is sampled at the chip rate T_c^{-1}. The lth sample of the pth bit is expressed as

$$r_l(p) = \int_{pT_b+(l-1)T_c}^{pT_b+lT_c} r(t)dt. \quad (5)$$

The sampled signals for the pth bit, i.e., $r_l(p), l = 1, \cdots, L$, are obtained, then the matrix $c(p)$ is updated by the RLS algorithm to minimize the following square error function.

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$$J(p) = \sum_{i=1}^{p} \lambda^{p-i} \sum_{l=1}^{L} (r_l(i) - T_c \sum_{k=1}^{K} c_{kl}(p) b_k(i))^2 \quad (6)$$

where λ is the forgetting factor and it takes $0 < \lambda \leq 1$ and $b_k(i)$ is the known training data which corresponds to the kth user's information bit. As a result, the following update equations can be obtained.

$$\boldsymbol{k}(p) = \frac{\boldsymbol{P}(p-1)\boldsymbol{b}(p)}{\lambda + \boldsymbol{b}^T(p)\boldsymbol{P}(p-1)\boldsymbol{b}(p)}, \quad (7)$$

$$\boldsymbol{c}(p) = \boldsymbol{c}(p-1) + \boldsymbol{k}(p)(\frac{1}{T_c}\boldsymbol{r}(p) - \boldsymbol{b}^T(p)\boldsymbol{c}(p-1)), \quad (8)$$

$$\boldsymbol{P}(p) = \frac{1}{\lambda}\{\boldsymbol{P}(p-1) - \boldsymbol{k}(p)\boldsymbol{b}^T(p)\boldsymbol{P}(p-1)\} \quad (9)$$

where $\boldsymbol{k}(p)$ is a $K \times 1$ gain vector, $\boldsymbol{P}(p)$ is a $K \times K$ correlation matrix, $\boldsymbol{b}(p)$ whose kth element is $b_k(p)$ is a $K \times 1$ training data vector, $\boldsymbol{r}(p)$ whose lth element is $r_l(p)$ is a $L \times 1$ chip matched filter output vector and $\boldsymbol{c}(p)$ whose (k, l)th element is $c_{kl}(p)$ is a $K \times L$ matrix. Each element $c_{kl}(p)$ is updated in parallel.

The matrix $\boldsymbol{c}(p)$ converges to the optimum Wiener solution, $\boldsymbol{Aa}$, as the number of iterations, p, approaches infinity [7], where $\boldsymbol{A}$ whose diagonal elements are A_k is a $K \times K$ diagonal signal amplitude matrix and $\boldsymbol{a}$ whose (k, l)th elements are a_{kl} is a $K \times L$ spreading sequence matrix. A coefficient $c_{kl}(p)$ converges to $A_k a_{kl}$, that is the product of the kth user's signal amplitude and the lth chip of the kth user's spreading sequence.

After the matrix $\boldsymbol{c}(p)$ converges, the external inputs and connection weights of the Hopfield network are determined by

$$I_i = 2\sum_{l=1}^{L} r_l(p) c_{il}(p), \quad (10)$$

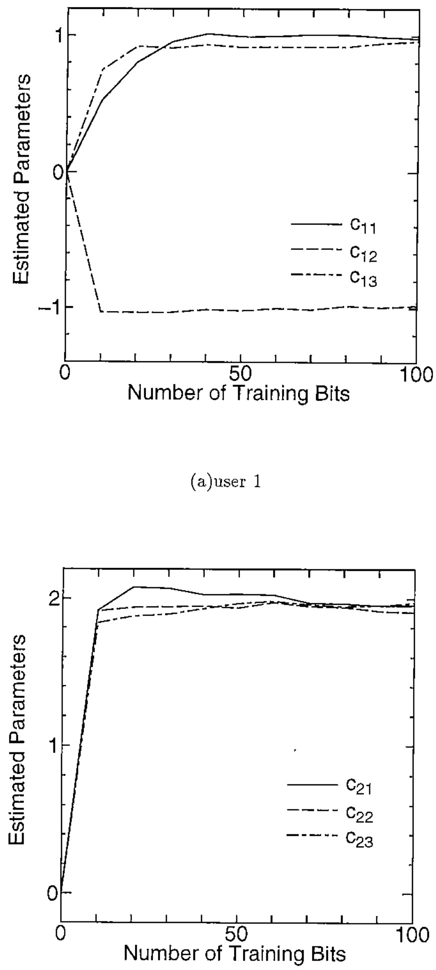
$$T_{ij} = -2\sum_{l=1}^{L} c_{il}(p) c_{jl}(p) T_c. \quad (11)$$

Then, information bit detection can be done by the dynamics of the Hopfield network as in cases these parameters are assumed to be known [2], [3].

3. Computer Simulation

To demonstrate the performance of the proposed receiver, we conducted simple computer simulation. It is assumed that $K = 2, L = 3, \lambda = 1, \boldsymbol{P}(0) = \boldsymbol{I}, \boldsymbol{c}(0) = \boldsymbol{o}$ and the spreading sequences for the 1st and 2nd user are $(+1, -1, +1)$ and $(+1, +1, +1)$. The energy of the ith user's signal is represented by E_i and the power spectral density of the channel noise is represented by N_0.

The estimated parameters are plotted in Fig. 1 where E_1/N_0 is 10 dB and $E_2/E_1 = 6\,dB(A_1 = 1, A_2 = 2)$. One can observe that the coefficients converge within several tens of training data bits. For example, the coefficient c_{21} approaches $A_2 a_{21} (= 2)$ as mentioned in the previous section. However, the coefficients are not equal to the Wiener solution since the number of iterations is finite.



(a)user 1

(b)user 2

Fig. 1 Parameter estimation.

Next, the performance of the proposed receiver is compared with that of the matched filter, optimum, and well-known adaptive receivers which include the minimum mean-square error (MMSE) [5] and multilayer neural network (MNN) receiver [6]. In the following simulation, it is assumed that both the matched filter and optimum receiver have the knowledge of both the amplitudes and spreading sequences. As for the MNN receiver, the number of layers is 3 and the numbers of input, hidden and output units are 3, 3 and 1, respectively. The MNN receiver is trained by the back propagation algorithm whose learning rate is 0.01 and momentum rate is 0.9. The MMSE receiver is trained by the LMS algorithm [4] whose step-size parameter is 0.1. The number of known training data for the proposed,

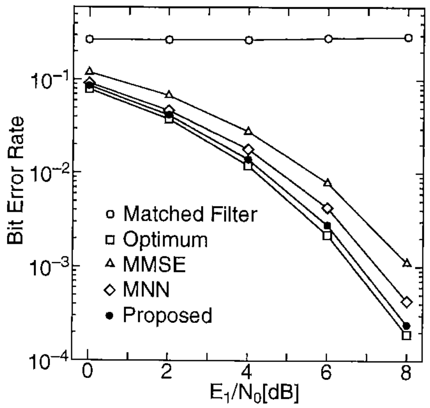


Fig. 2 Bit error rate versus E_1/N_0.

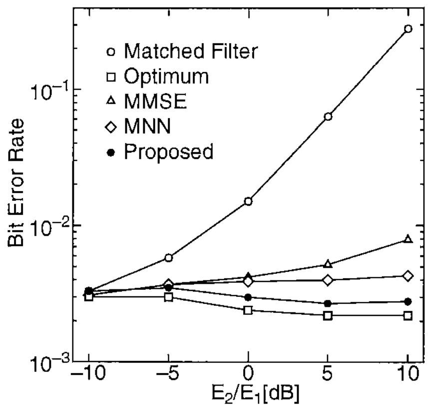


Fig. 3 Bit error rate versus E_2/E_1.

MMSE and MNN receiver are 40, 100 and 10000, respectively. These parameters were determined by preliminary simulation results. Figure 2 shows bit error rates of the 1st user as a function of E_1/N_0 where E_2/E_1 is 10 dB. In Fig. 3, bit error rates of the 1st user as a function of E_2/E_1 are depicted where E_1/N_0 is 6 dB. The matched filter receiver suffers performance degradation because of severe near-far problem. The performance of the MMSE receiver is better than that of the matched filter receiver, but is far from that of the optimum receiver. It is known that nonlinear structure is needed to obtain the optimum performance in near-far situations [6]. However, since the MMSE receiver is based on linear transform of the received signal, it can not achieve the optimum performance. On the other hand, the MNN receiver has nonlinear structure. However, since the back propagation algorithm tends to trap into spurious local minima, it is hard to achieve the optimum performance. Thus, the performance of the MNN receiver is worse than that of the optimum receiver. The proposed receiver has nonlinear structure in the Hopfield network and the global convergence of the training algorithm is ensured. Although the performance of the proposed receiver is slightly worse than that of the optimum receiver since the number of training data is finite, the performance is near optimum.

4. Conclusions

An adaptive multiuser receiver using a Hopfield network has been proposed. Moreover, performance comparisons with the matched filter, optimum, MMSE and MNN receiver have been carried out via computer simulation. Since the parameters considered in the simulation are not practical, the performance evaluations for more practical situations, e.g., the number of users is large, the length of the spreading sequence is long and a fading channel, are needed. Moreover, performance analysis of the proposed receiver is our future problem.

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