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On the Multiuser Detection Using a Neural Network in Code-Division Multiple-Access Communications

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SUMMARY In this paper we consider multiuser detection using a neural network in a synchronous code-division multiple-access channel. In a code-division multiple-access channel, a matched filter is widely used as a receiver. However, when the relative powers of the interfering signals are large, i.e. the near-far problem, the performances of the matched filter receiver degrade. Although the optimum receiver for multiuser detection is superior to the matched filter receiver in such situations, the optimum receiver is too complex to be implemented. A simple technique to implement the optimum multiuser detection is required. Recurrent neural networks which consist of a number of simple processing units can rapidly provide a collectively-computed solution. Moreover, the network can seek out a minimum in the energy function. On the other hand, the optimum multiuser detection in a synchronous channel is carried out by the maximization of a likelihood function. In this paper, it is shown that the energy function of the neural network is identical to the likelihood function of the optimum multiuser detection and the neural network can be used to implement the optimum multiuser detection. Performance comparisons among the optimum receiver, the matched filter one and the neural network one are carried out by computer simulations. It is shown that the neural network receiver has a capability to achieve near-optimum performance in several situations and local minimum problems are few serious.

key words: *recurrent neural networks, code-division multiple-access, near-far problem, optimum multiuser detection.*

1. Introduction

In a code-division multiple-access(CDMA) system, several independent users share simultaneously a common channel using preassigned code waveforms. The conventional signal detection technique in a multiuser channel uses matched filters because the filters are simple to implement. It is known that when the relative powers of the interfering signals are large, i.e. the near-far problem, the performance of the conventional matched filter receiver degrades since the receiver is designed with ignoring the presence of interfering signals. To overcome this problem, the optimum multiuser detection in a synchronous CDMA system has been developed [1]. The optimum multiuser detection can be carried out by the maximization of a likelihood function. Although the receiver for the optimum multiuser detection is superior to the conventional receiver, the receiver requires computational complexity which grows exponentially with increasing the number of users. Since there would be a number of users in a CDMA system, it may be impractical to implement the optimum detection. Therefore a simple technique to implement the optimum multiuser detection is required.

Low complexity multiuser detectors that provide near-optimum performance have been proposed [1], [2]. Lupas et.al. [1] proposed the linear multiuser detectors which are based on linear transformations of a bank of matched filter outputs. Varanasi et.al. [2] proposed the multi-stage detectors which are based on a strategy of successive multiple-access interference rejection. The computational complexity of these detectors is proportional to the number of users.

In this paper, multiuser detection using a neural network in a synchronous CDMA channel is considered. Neural networks provide high computational rates because a large number of simple nonlinear processing units which constitute a neural network operate in parallel. Neural networks may be mainly classified into the multilayer neural network and the recurrent one.

The multilayer neural network consists of several layers of processing units. The network acts as an adaptive system and can approximate any continuous mapping. Thus the network has been successfully used in various fields such as speech recognition and pattern classification [3]. Since the signal detection problem can be regarded as the pattern classification problem, the multilayer neural network can be used for signal detection [4]. Recently Aazhang et.al. [5] proposed a new class of multiuser detection system in CDMA channels which uses the multilayer neural network. There are some problems when the multilayer neural network is used for the multiuser detection. Firstly, it is not known how many units in the hidden layer are needed. Secondly, the known training sequences are required to train the network. Moreover, in general, it is not clear that how many symbols are needed for training. Thirdly, it is difficult to determine the learning rate appropriately. Lastly, as for the back propagation which is widely used to train multilayer neural

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networks, it is not guaranteed to find the global minimum of the error surface. It is difficult to set these parameters optimum. If the optimum parameters are determined, the receiver using the multilayer neural network is able to perform the optimum detection. However, if these parameters are determined empirically, the receiver can be expected to perform the quasi-optimum detection since many good results have been obtained in pattern classification problems [3]. In practice, Aazhang et.al. [5] reported that the performance of the receiver using the multilayer neural network is better than that of the conventional receiver and is comparable to that of the optimum one.

On the other hand, as for the recurrent neural network, Hopfield [6] proved that the recurrent neural network where a processing unit is connected to each other converges to a minimum of the energy function. The receiver using the recurrent neural network has never been proposed. The purpose of this paper is to propose the receiver using the recurrent neural network and compare the performance of the receiver with that of the optimum receiver. It is the very interesting point that the energy function of the network is identical to the likelihood function of the optimum multiuser detection and the recurrent neural network can be used to implement the optimum multiuser detection.

The outline of this paper is as follows. In Sect. 2, we describe the optimum multiuser detection in a synchronous CDMA channel. We explain the recurrent neural network and propose the receiver using the recurrent neural network in Sect. 3. In Sect. 4, we present the numerical results. Finally, in Sect. 5, we summarize the main results.

2. Optimum Multiuser Detection

In this section, we describe the optimum multiuser detection in a synchronous CDMA channel. It is assumed that there are K users in a channel and the kth user is assigned a signature waveform which is denoted $s_k(t)$, $t \in [0, T]$ where T is the symbol duration. The assigned signature waveform can be written as

$$s_k(t) = A_k a_k(t) \cos(\omega_c t + \theta_k), \qquad k = 1, 2, \cdots, K \tag{1}$$

where A_k is the signal amplitude, ω_c is the carrier frequency, $\theta_k \in [0, 2\pi)$ is the phase angle and $a_k(t)$, whose length is N, is the spreading code assigned to the kth user. The received energy per bit of the kth user's signature waveform, denoted E_k, is not always equal to that of another user's one due to the near-far problem where the relative received powers of the interfering signals become large. The received signal in a synchronous CDMA system with additive channel noise, denoted $r(t)$, can be written as

$$r(t) = \sum_{k=1}^{K} b_k s_k(t) + n(t) \tag{2}$$

where $b_k \in \{+1, -1\}$ is the kth user's information bit and $n(t)$ represents the additive white Gaussian noise.

In more general asynchronous CDMA systems, there are relative time delays, τ_k, among the K signals, and $s_k(t)$ in Eq. (2) becomes $s_k(t-\tau_k)$. As we consider a synchronous CDMA system in this paper, the relative time delays are assumed to be zero, i.e. $\tau_k = 0$ $\forall k$.

Consider the demodulation of the transmitted information bit. The output of a matched filter which matches the kth user's signature waveform, denoted y_k, can be written as

$$y_k = \int_0^T r(t) s_k(t)\, dt, \qquad k = 1, 2, \cdots, K. \tag{3}$$

The conventional matched filter detection is based on sign of y_k

$$\hat{b}_k = \mathrm{sgn}\, y_k. \tag{4}$$

Note that in Eq. (4) the multiple-access interference is ignored.

The optimum detection can be carried out by selecting the most likely information vector, $\hat{\boldsymbol{b}} = (\hat{b}_1, \cdots, \hat{b}_K)$, $\hat{b}_k \in \{+1, -1\}$, which maximizes the following likelihood function [1]

$$L = \sum_{i=1}^{K} 2 y_i \hat{b}_i - \sum_{i=1}^{K} \sum_{j=1}^{K} h_{ij} \hat{b}_i \hat{b}_j \tag{5}$$

where h_{ij} is cross-correlation between the preassigned waveforms:

$$h_{ij} = \int_0^T s_i(t) s_j(t)\, dt. \tag{6}$$

Note that h_{ii} is the energy-per-bit and $h_{ii} \neq 0$. The maximization problem of L has been shown to be NP-complete [1]. No algorithm which can solve the maximization problem in polynomial time in K is known. Thus implementation of the optimum multiuser detection is impractical when the number of users is large. A simple technique to achieve near-optimum performance is needed.

3. Multiuser Detection Using a Neural Network

In this section, we describe the recurrent neural network and the relation between the optimum multiuser detection and the network. Moreover, the receiver using the neural network (the neural network receiver) is proposed.

3.1 Recurrent Neural Networks

The recurrent neural network consists of a large number of simple nonlinear processing units. In the network, each unit is connected to each other, i.e. the output of each unit is fed to all other units via connectinon weights, and each unit has an external input. The output of each unit is determined by first summing all of the inputs and then applying a nonlinear transformation. The equation of motion describing the time evolution of the network is:

$$\frac{du_i}{dt} = -\frac{u_i}{\tau} + \sum_{j=1}^{M} T_{ij}V_j + I_i \tag{7}$$

where u_i is a potential of the ith unit, V_i is an output of the ith unit, T_{ij} is a connection weight from the jth unit to the ith one, I_i is an external input to the ith unit, τ is a time constant and M is the number of the units. The output of the ith unit is defined as:

$$V_j = \tanh(u_j) \tag{8}$$

Hopfield [6] showed that when connection weights are symmetric, i.e. $T_{ij} = T_{ji}$, the equations of motion always lead to stable states, where the outputs of all the units remain constant. The stable states are the global or local minima of the quantity

$$E = -\sum_{i=1}^{M} V_i I_i - \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M} T_{ij}V_iV_j. \tag{9}$$

E is called energy function. The time derivative of the energy function is always negative. This type of the network has been successfully used in such an optimization problem as the Traveling-Salesman Problem [7]. In spite of NP-complete, the network can rapidly provide a solution. Note that the solution is not always the best solution but is the quasi-best one.

In this paper, we consider the ideal case where a time constant τ is infinity. When τ is infinity, the first term in Eq. (7) becomes negligible. Moreover we assume that the self-connections T_{ii} are 0. It is known that the state of the network always converges to a corner of the hyper cube under these assumptions [8]. V_i is 1 or -1 at each corner of the hyper cube. Thus these assumptions are natural for a binary problem considered in this paper.

It should be noted that the assumption that is $T_{ii} = 0$ does not affect searching of a state which minimize the energy function at each corner of the hyper cube. As a binary problem is investigated, one should consider the energy at each corner of the hyper cube. A contribution of the self-connections to the energy function is given by $\sum_{i=1}^{M} T_{ii}V_i^2$. The contribution is constant because $V_i^2 = 1$ at the corner of the hyper cube. Therefore the relations between the energies at all the corners can be maintained even if the self-connections are 0. Moreover, as mentioned above, the state of the network always converges to one of corners of the hyper cube and the state does not converge to interior of the hyper cube. Consequently, one can search a state which minimize the energy function at each corner of the hyper cube.

3.2 Multiuser Detection Using a Neural Network

We have described that the optimum multiuser detection problem is the maximization of the likelihood function L and the dynamics of the neural network is the minimization of the energy function E. Here we should notice the relation between the optimum multiuser detection and the neural network.

As for the optimum multiuser detection, it is clear that the maximization of L is the minimization of the quantity

$$L' = -\sum_{i=1}^{K} 2y_i\hat{b}_i + \sum_{i=1}^{K}\sum_{j=1}^{K} h_{ij}\hat{b}_i\hat{b}_j \tag{10}$$

The optimum multiuser detection can be clearly related to the neural network by identifying L' and E. As a result, the variables correspond as follows:

$$I_i = 2y_i \tag{11}$$

$$T_{ij} = -2h_{ij} \tag{12}$$

$$V_i = \hat{b}_i \tag{13}$$

$$M = K. \tag{14}$$

The external input to the ith unit is given by the output of the ith matched filter. The connection weight from the jth unit to the ith one is given by crosscorrelation between the preassigned waveform to the jth user and that to the ith one. After the dynamics of the network converged, i.e. the outputs of the units do not change, the output of the ith unit corresponds to estimation of the information bit transmitted by the ith user. And the number of the units in the neural network is equal to that of the users in the CDMA system. Thus the neural network receiver is shown in Fig. 1. Each open circle is a processing unit.

Note that E is equal to L' only when $V_i = \pm 1$. $\hat{b}_i$ in L' can be a binary value $\{-1, 1\}$. On the other hand, V_i in E can be a real value in the range of $[-1, 1]$. Thus one should consider the energy E when V_i is

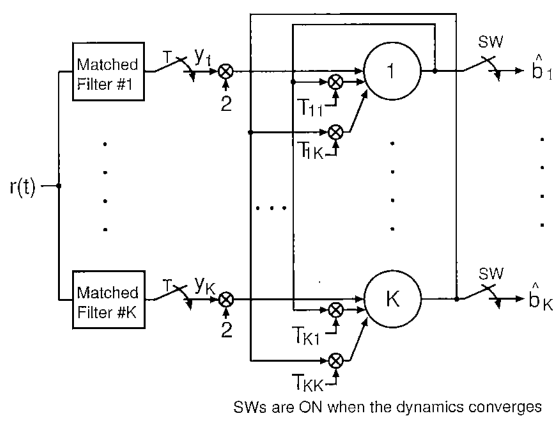

Fig. 1 Structure of the neural network receiver.

a value in the rage of $(-1, 1)$. However, as mentioned above, when τ is infinity and T_{ii} are 0, the state of the network always converges to a corner of the hyper cube. Thus one can neglect the energy inside the hyper cube. Moreover, when $T_{ii}=0$, since the relations between the energies at all the corners can be maintained, then the state which minimize E is equal to the information vector which minimize L'.

As mentioned in the previous section, the self-connections in the neural network of the receiver are the energy-per-bit and these are not 0. However, due to the reason mentioned above, the self-connections are set 0, i.e. $T_{ii}=0 \forall i$.

As mentioned above, the connection weights must be symmetric to converge. Fortunately, the connection weights in the neural network of the receiver are symmetric, because both h_{ij} and h_{ji} are cross-correlation between the preassigned waveform to the jth user and that to the ith one. Consequently, the likelihood function L' can be minimized by the dynamics of the neural network.

It is noted that the optimum detection can be achieved only when the stable state which the network converges to is the global minimum of E. However, it is only ensured that the network converges to one of minima of the energy function. The minimum is not always the global minimum and may be a local one. If the neural network of the receiver converges to the local minimum, the performance of the receiver may degrade. However, even if the network converges to the local minimum, the local minimum can be expected to be roughly the same as the global one, i.e. the solution obtained by the network may be the quasi-best solution, as shown in the Traveling-Salesman Problem [7]. Thus the neural network receiver is expected to provide near-optimum performance.

The choice of the initial values of the unit output voltages is very important because it determines which minimum (the global minimum or local minimum) the network converges to. It is known that when the number of the units is two, the best solution, i.e. the gbobal minimum, can be obtained if the initial values of the unit output voltages are at the origin of the state space [8]. Thus in this paper the initial values of the unit output voltages can be 0, i.e., $V_i=0 \forall i$, regardless of the number of units.

Unlike multilayer neural networks, iterative training such as the back propagation is not required to determine the connection weights of the recurrent neural network of the receiver. The connection weights are determined by Eq. (12).

4. Numerical Results

Performance comparisons among the optimum receiver, the matched filter one and the neural network one are carried out by computer simulations. The main purpose of the simulations is to show the neural network receiver can achieve near-optimum detection in various situations. In two-user channel case, the receiver using the multilayer neural network which is proposed by Aazhang et. al. [5] is also considered. The simulations used an equivalent lowpass system. It is assumed that the estimation of the carrier phase is obtained.

4.1 Two-User Channel

Firstly, we consider a synchronous two-user Gaussian channel. In this example, we make sure of the behavior of the neural network receiver. The number of the units is two since the number of units is equal to that of users. As mentioned in the previous section, when the number of the units is two, it is ensured that a network converges to the global minimum of the energy function. As a result, the neural network receiver could achieve the optimum performance. The spreading sequence of the first user is a maximal length sequence of length $N=31$ and that of the second user is the image sequence of the first user's one.

As for the multilayer neural network, the input signals to the network are obtained by sampling the output of the front-end filter at the chip rate. The number of the units in the hidden layer is three. The back propagation is used as a training algorithm. The learning rate is 0.1, the momentum rate is 0.9 and the length of training periods is 10,000 symbols.

Figure 2 shows the bit error rates (BER) of the first user versus the energy per bit of the first user E_1 to the power spectral density of noise N_0 ratio where the relative energies of the two users are fixed to $E_2/E_1=6$ dB. The BER of the matched filter receiver is worse than that of the optimum receiver because of the near-far problem. As expected above, the network always converges to the global minimum, and the BER of the neural network receiver is exactly the same as that of the optimum one. The performance of the receiver using the multilayer neural network is better than that of the matched filter one and is near optimum

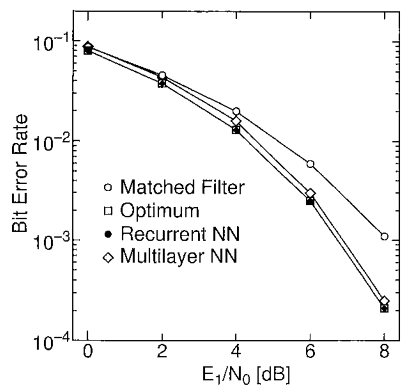

Fig. 2 Bit error rate versus E_1/N_0 for a two-user channel with $E_2/E_1=6$ dB.

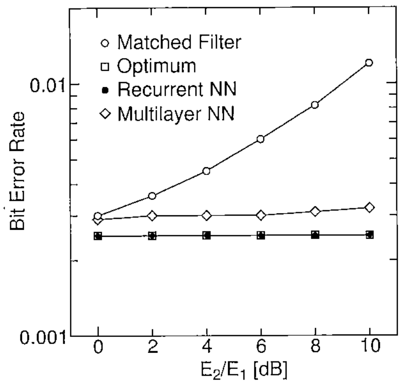

Fig. 3 Bit error rate versus E_2/E_1 for a two-ser channel with $E_1/N_0=6$ dB.

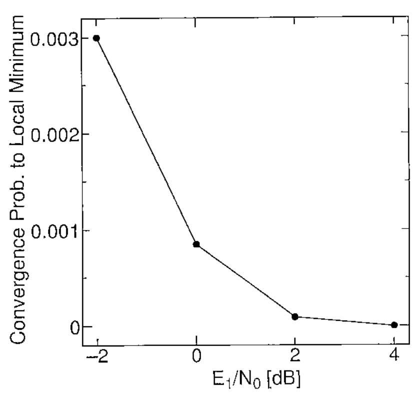

Fig. 4 Convergence probability to local minimum versus E_1/N_0 for a six-user channel with $E_i/E_1=6$ dB.

performance. However, it is noted that the performance of the multilayer neural network receiver is slightly worse than that of the recurrent neural network one.

Figure 3 shows the BER versus the relative energies of the two users under $E_1/N_0=6$ dB. The BER of the matched filter receiver becomes worse as the energy of the interfering user increases because the receiver ignores the multiple-access interference. On the other hand, the BER of the optimum receiver is not affected by the energy of the interfering user. Moreover, the network always converges to the global minimum and the BER of the receiver is equal to that of the optimum one. The performance of the receiver using the multilayer neural network has near optimum performance but the performance is worse than that of the recurrent neural network.

4. 2 Six-User Channel

Next, we consider a synchronous six-user Gaussian channel. In this example, we consider the convergence probability to the local minimum and its effect on the BER performance. In particular, we consider the convergence probability against the signal-to-noise-ratio and the relative energies of users. The spreading sequences of the first and second user are the same as those of the two-user channel example, and those of the third user and fourth user are different ones of maximal length sequences of length $N=31$ and those of the fifth and sixth user are the image sequences of that of the third and fourth user respectively. It is assumed that the users except the first user have equal energy.

Unlike the two-user channel, a few convergences to the local minimum were observed. Figure 4 depicts the convergence probability to the local minimum versus E_1/N_0 where the energy of the ith user E_i to that of the first user E_1 ratio is $E_i/E_1=6$ dB. The convergence probability to the local minimum becomes large as the E_1/N_0 decreases. As described above, the convergence to the local minimum is expected to degrade the

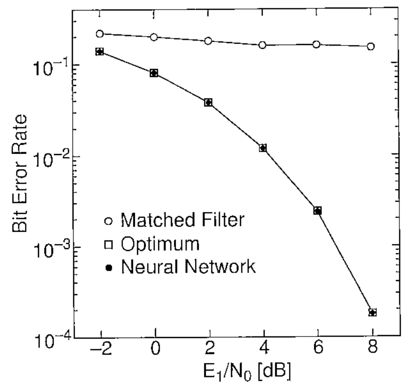

Fig. 5 Bit error rate versus E_1/N_0 for a six-user channel with $E_i/E_1=6$ dB.

performance. The BER of the first user versus E_1/N_0 is shown in Fig. 5 to show the convergence effect on the BER performance. Performance degradation of the matched filter receiver is observed due to severe near-far problem particularly in high E_1/N_0. In spite of the convergence to the local minimum, the BER of the neural network receiver is nearly equal to that of the optimum one over the range of E_1/N_0. It is noted that although the convergence probability is high when E_1/N_0 is low, these situations have no interest. Because the performance of the matched filter receiver is similar to that of the optimum one when E_1/N_0 is low, and we have few benefits of the optimum detection.

Next, the near-far effect in the six-user channel is considered. The convergence probability to the local minimum versus the strength of the interfering signals relative to that of the first user's signal E_i/E_1 is shown in Fig. 6 under $E_1/N_0=6$ dB. A few convergences to the local minimum are observed when the strength of the interfering signals are weak. The BER of the first user versus E_i/E_1 is shown in Fig. 7. In the same way as the two-user channel, the performance of the matched filter receiver becomes worse as the strength of the interfering signals increases. On the other hand, the optimum receiver can eliminate the multiple-access

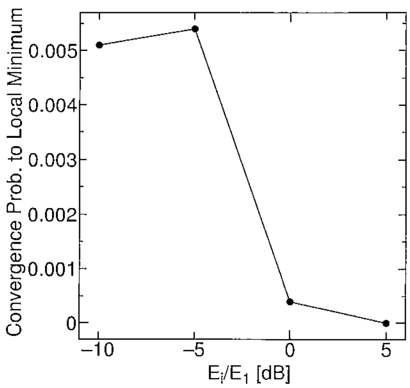

Fig. 6 Convergence probability to local minimum versus E_i/E_1 for a six-user channel with $E_1/N_0=6$ dB.

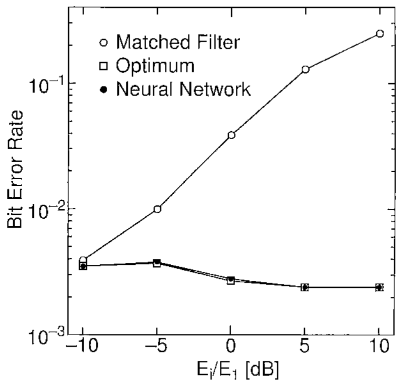

Fig. 7 Bit error rate versus $E_i//E_1$ for a six-user channel with $E_1/N_0=6$ dB.

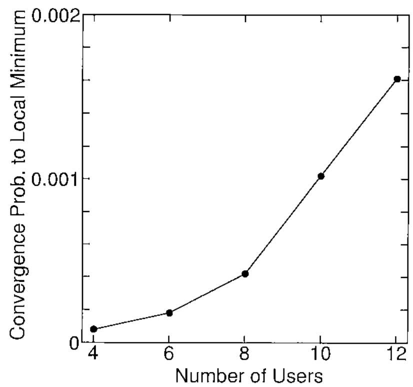

Fig. 8 Convergence probability to local minimum versus the number of users($E_i/E_1=-3$ dB, $E_1/N_0=0$ dB).

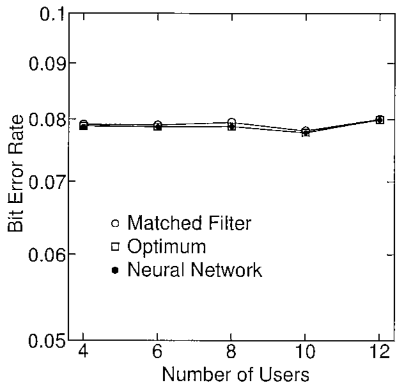

Fig. 9 Bit error rate versus the number of users($E_i/E_1=-3$ dB, $E_1/N_0=0$ dB).

interference over the range of E_i/E_1. The BER performance of the neural network receiver is similar to that of the optimum one. Note that although the convergence probability increases when E_i/E_1 is low, these situations have no interest since there are few gains of the optimum detection. Thus it can be concluded that the convergence to the local minimum is few serious. We would rather emphasize the network hardly converges to the local minimum in the interesting case where both E_1/N_0 and E_i/E_1 are high.

4. 3 K-User Channel

Lastly, we consider a synchronous K-user Gaussian channel. In this example, we consider the convergence probability to the local minimum against the number of users and its effect on the BER performance. To study the effect of the convergence to the local minimum is important when the number of users increases. Because the number of minima increases as that of the units (corresponds to that of users) increases [9]. The spreading sequence of the first user is the same as that of the two-user channel example, and those of other users are shifted ones of the first user's one.

In the first example, the relative energies are $E_i/E_1=-3$ dB and the signal-to-noise-ratio is $E_1/N_0=0$ dB. These parameters are chosen as relatively low to study the convergence probability to the local minimum. The convergence probability is shown in Fig. 8 as a function of the number of users. The convergences to the local minimum are observed when the number of users are large. The BER of the first user is illustrated in Fig. 9 as a function of the number of users. The optimum performance can be achieved by the neural network receiver even if the number of users is large. On the other hand, the BER of the matched filter receiver is nearly equal to that of the optimum one because both E_i/E_1 and E_1/N_0 are low. Thus the optimum receiver is not already needed in such trivial situations.

Now we should consider the interesting case where the optimum receiver significantly outperforms the matched filter one. We choose both E_i/E_1 and E_1/N_0 are relatively high, E_i/E_1 and E_1/N_0 are 10 dB and 6 dB respectively. Figure 10 shows the BER performances versus the number of users. The BER performance of the matched filter receiver becomes worse with increasing the number of users. The BER of the neural network receiver is the same as that of the optimum one. The convergence to the local minimum

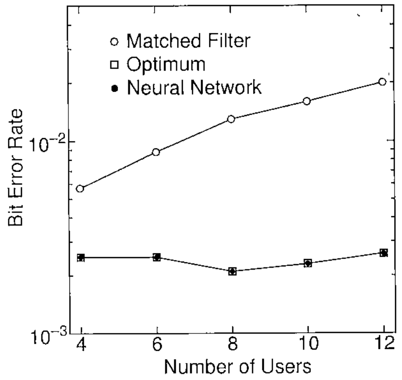

Fig. 10 Bit error rate versus the number of users ($E_i/E_1=10$ dB, $E_1/N_0=6$ dB).

is not observed regardless the number of users. Therefore the convergence probability to the local minimum in the interesting case is less sensitive to the increase of the number of users than that in the previous trivial case. Although the number of users considered here may be small, these results indicate that the multiuser detection using a neural network is an attractive technique to achieve near-optimum performance.

5. Conclusions

In this paper, we considered the multiuser detection using a recurrent neural network in synchronous code-division multiple-access channels. It was shown that the energy function of the network is identical to the likelihood function of the optimum detection and the recurrent neural network can be used to implement the optimum multiuser detection. Performance comparisons among the optimum receiver, the conventional matched filter one and the neural network one were carried out by computer simulations.

The convergence to the local minimum had been expected to degrade the performance of the neural network receiver. However, the network hardly converged to the local minimum in the case of interest. The receiver could achieve near-optimum performance even if the network converged to the local minimum. Moreover, it was shown that the convergences are few serious, because the convergences were observed when the signal-to-noise-ratio is low or the relative energies of users are small and there are few gains of the optimum detection in such cases. Furthermore, it was shown that the convergence probability in the interesting case is less sensitive to the increase of the number of users than that in the trivial case. The number of the users considered in this paper may be small, however, these results indicate that the neural network receiver can achieve near-optimum performance in the case of interest.

The situation considered in this paper is an example of CDMA communications. More considerations in various situations are required. Moreover, we must analyze the performances of the neural network receiver.

It is well known that the simulated annealing is the method which is ensured to converge to the global minimum [10]. Thus if the simulated annealing is used, there is no problem for the local minimum. However, the method has the disadvantage of slowness. On the other hand, there are many simple techniques to improve the convergence probability to the global minimum [11], [12]. It is a future work to consider performance improvement of the neural network receiver using these techniques.

The neural network receiver may be implemented by using a neuro-chip which is being rapidly developed. Hardware implementation of the receiver is an our future work.

We should refer briefly to the multilayer neural network receiver. In this paper, the performances of the receiver using the multilayer neural network were shown only in the two-user channel case. Although the results were not shown in the six-user channel and in the K-user channel, simulations have been carried out. Like in the two-user channel, the performances of the receiver using the multilayer neural network are near optimum performances but the performances are worse than those of the recurrent neural network one and those of the optimum one. For example, as to E_1/N_0 under the BER 10^{-2}, the multilayer neural network receiver is worse about 1.5 dB than the recurrent one in the six-user case. The result is an example. The optimum performances will be obtained by setting parameters optimum. However, the optimization is difficult, and we can conclude that the multilayer neural network is hard to use. On the other hand, the recurrent neural network receiver has no parameter and does not need training. Thus the recurrent neural network receiver is easier to use than the multilayer one.

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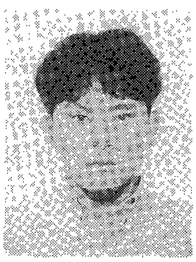

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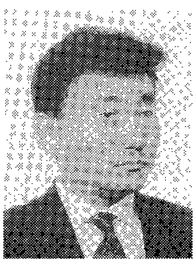

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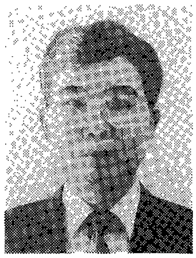

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