

Title	Channel identification and sequential sequence estimation using antenna array in broadband mobile communications
Author(s)	Matsumoto, T.
Citation	1999 2nd IEEE Workshop on Signal Processing Advances in Wireless Communications, 1999. SPAWC '99.: 403-406
Issue Date	1999-05
Type	Conference Paper
Text version	publisher
URL	http://hdl.handle.net/10119/4821
Rights	Copyright (c)1999 IEEE. Reprinted from 1999 2nd IEEE Workshop on Signal Processing Advances in Wireless Communications, 1999. SPAWC '99. This material is posted here with permission of the IEEE. Such permission of the IEEE does not in any way imply IEEE endorsement of any of JAIST's products or services. Internal or personal use of this material is permitted. However, permission to reprint/republish this material for advertising or promotional purposes or for creating new collective works for resale or redistribution must be obtained from the IEEE by writing to pubs-permissions@ieee.org . By choosing to view this document, you agree to all provisions of the copyright laws protecting it.
Description	

CHANNEL IDENTIFICATION AND SEQUENTIAL SEQUENCE ESTIMATION USING ANTENNA ARRAY IN BROADBAND MOBILE COMMUNICATIONS

Tadashi Matsumoto

NTT Mobile Communications Network Inc.
3-5 Hikari-no-Oka, Yokosuka, Kanagawa 239-8536, Japan

ABSTRACT

This paper proposes the joint use of antenna array and sequential sequence estimation (SSE) technique for the equalization of multipath fading channels suffering from severe ISI. It is shown that with the proper use of the Multiple Stack Algorithm (MSA), exploiting the redundant structure of the signal received by multiple antenna array elements can enhance the uniqueness of the sequence estimation, thereby significantly reducing the frame erasure probability. Three new algorithms are derived for vector channel identification, the results of which are used to calculate the Fano metric for SSE. The first algorithm uses just a temporal reference, and others use both temporal and spatial references. Impacts of using the temporal and spatial references are investigated in terms of the channel identification accuracy as well as overall frame erasure rate (ERR) and bit error rate (BER). Results of computer simulations are presented to compare the performances of the three algorithms.

1. INTRODUCTION

Inter-symbol interference (ISI) imposed on received signals has long been a chief hurdle target to overcome when very high speed signal transmission is required over mobile communication channels. The radio signal propagation in mobile communications is subjected to multipath fading, in which the complex envelope of each propagation path varies with the vehicle's movement. Hence, the ISI caused as a result of multipath propagation is time-variant.

Delayed decision feedback sequence estimation (DDFSE) proposed by Ref. [1], [2] is based on the combined use of maximum likelihood sequence estimation (MLSE) and the decision feedback equalizer (DFE). The computational complexity of DDFSE is dominated by the MLSE part since the complexity with MLSE is exponentially proportional, whereas that with DFE is merely proportional, both to the channel memory length v . Overall performance of DDFSE equalizers is, on the contrary, dominated by the DFE part because DFE signal detection is made based on one-shot observation of the equalized signal which is, in many cases, unreliable. A disadvantageous outcome of the feedback of such unreliable decision results is the error propagation.

The potential of the sequential sequence estimation (SSE) technique for ISI equalization was indicated in Ref. [3], [4]. The computational effort needed for the sequential search process is almost independent of v . It is mainly dependent on the channel condition: fewer computations are required to complete the sequence search in better channel conditions. Hence, SSE is considered effective in reducing time-variant ISI if the adaptive channel identification capability can be incorporated within SSE.

Theoretically, SSE performance is asymptotically equivalent to that of MLSE if unlimited computation capability is available. However, if decoding is not completed within the time allotted, buffer overflow happens and the frame being processed is erased. In practice, at a cost of appreciable performance degradation

from the asymptotic performance, practical algorithms [5]-[6] may be used, which, instead of trying full search, output tentative decisions if buffer overflow happens, and hence lower erasure rates (ERR) are achieved.

Given the time-variant nature of the multipath fading channel, the estimate of the transmitted sequence may not be uniquely determined even in the absence of noise: more than one sequence with length $v+1$ (= the number of the propagation path) can result in the same received signal point for some sets of complex envelopes on propagation paths. In fact, it is likely that some of the sequence estimates result in different signal points but they are very close to each other in the complex domain. In the presence of noise, this makes it difficult to uniquely estimate the transmitted sequence. Hence, even with the low-ERR SSE algorithms being used for ISI equalization, buffer overflow still is a major cause of error.

The goal of this paper is to reduce the erasure probability of SSE for ISI equalization even in the presence of the severe ISI caused by multipath propagation. For this purpose, this paper proposes the use of an antenna array. This is because the differences in the received signal phases between the antenna elements depend on each signal's incident angle, and it is very unlikely that all received signal components have the same incident angles. Therefore, even if the uniqueness of sequence estimates is collapsed at some of the antenna elements it is likely to remain at the others.

This paper derives three new algorithms for vector channel identification, and compares their performances. The first algorithm uses just a temporal reference. The array response vectors for each of the path components are estimated by using unique word sequences whose waveform and timing are assumed to be known to both the transmitter and receiver as the temporal reference. The other two algorithms examined in this paper use both temporal and spatial references, where knowledge about the direction-of-arrival's (DOA's) of each path component is assumed to be available as the spatial reference.

This paper is organized as follows: Section 2 shows the system model used in this paper, and describes mathematical expressions for each component of the model. Section 3 describes details of the three channel identification algorithms. Section 4 presents results of computer simulations conducted to evaluate the ISI equalization performance of the three algorithms where the multiple stack algorithm (MSA) is used as a low-ERR SSE scheme.

2. SYSTEM MODEL

(A) Channel

Figure 1 shows, for the equivalent complex baseband domain, a block diagram of the system considered in this paper. The transversal filter model is used to express the multipath channel, as in Refs. [3], [4], where the transversal filter has $v+1$ (=J) taps with spacing equal to the symbol duration T . The only difference from the references is that in this paper each propagation path is associated with incident angle θ .

There is only one user sharing the channel. The signal is received by a K -element antenna array. Because of the multipath propagation, the received composite signal suffers from severe ISI. A discrete-time expression of the K -dimensional vector channel is, with n being the symbol timing index, given by

$$\mathbf{y}(n) = \mathbf{r}(n) + \mathbf{g}(n) \quad (1)$$

where $\mathbf{y}(n) = [y_1(n), y_2(n), \dots, y_L(n)]^t$ is the receiver output vector,

$$\mathbf{r}(n) = \sum_{j=0}^v \mathbf{a}(\theta) z_j(n) x(n-j) \quad (2)$$

is the antenna array output vector in the absence of noise, $J=v+1$ is the number of the propagation path, θ_j is the j -th path's DOA, $\mathbf{a}(\theta)$ is the array response vector for the path arriving at angle θ , $z_j(n)$ is the fading complex envelope with the j -th path, and $x(n)$ is the transmitted symbol. Assuming that the receiver filter satisfies Nyquist's ISI-free condition at every symbol timing, $\mathbf{g}(n)$ is a sample vector of the white additive Gaussian noise (AWGN). Practicality is not lost by assuming that each of $\mathbf{z}_g(n)$'s K elements has equal power σ_g^2 , and that the value of σ_g^2 is known to the receiver. $\langle |z_j(n)|^2 \rangle = \sigma_j^2$ is the j -th path's average power and $\Gamma = \sigma^2 / \sigma_g^2$ is, with $\sigma^2 = \sigma_0^2 + \sigma_1^2 + \dots + \sigma_v^2$, the per-element average received signal-to-noise power ratio (SNR).

(B) Receiver

For notation convenience, let the term $z_j(n)\mathbf{a}(\theta_j)$, $0 \leq j \leq v$, in Eq. (2) be denoted by $\mathbf{A}_{c_j}(n)$'s. Then, define $K \times J$ matrix $\mathbf{A}(n)$ as

$$\mathbf{A}(n) = \begin{bmatrix} \mathbf{A}_{c_0}(n) & \mathbf{A}_{c_1}(n) & \dots & \mathbf{A}_{c_v}(n) \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{r_1}(n) \\ \mathbf{A}_{r_2}(n) \\ \vdots \\ \mathbf{A}_{r_K}(n) \end{bmatrix}, \quad (3)$$

where $\mathbf{A}_{r_k}(n)$'s, $1 \leq k \leq K$, are the row vectors of $\mathbf{A}(n)$. The reliability comparison among candidate sequences with different lengths relies on the Fano metric given by

$$L[\mathbf{x}_i, \mathbf{Y}] = \sum_{n=1}^{N_i} L[\mathbf{r}(n), \mathbf{y}(n)] \quad (4)$$

where $\mathbf{x}_i = [x_i(1), x_i(2), \dots, x_i(N_i)]$ is the i -th candidate of the transmitted symbol sequence with length N_i ; and $\mathbf{Y} = [y(1), y(2), \dots, y(N_i)]$ is the received signal vector sequence. $L[\mathbf{r}(n), \mathbf{y}(n)]$ is a branch metric that is, for an equally likely M -ary input sequence, given by [6]

$$L[\mathbf{r}(n), \mathbf{y}(n)] = \frac{1}{\ln 2} \left(\rho[n, \mathbf{x}_{Tm}] - \ln \sum_{m=1}^{M'} \exp \left\{ \rho[m, \mathbf{x}_{Tm}] \right\} \right) + J - \log_2 M \quad (5)$$

with

$$\rho[m, \mathbf{x}_{Tm}] = \frac{1}{2\sigma^2 \ln 2} \sum_{k=1}^K \left| y_k(n) - \mathbf{A}_{r_k}(n) \mathbf{x}_{Tm}(n) \right|^2 \quad (6)$$

where $\mathbf{x}_{Tm}(n)$ is the vector comprised of the m -th sequence's last J entries, i.e., $\mathbf{x}_{Tm}(n) = [x_m(n), x_m(n-1), \dots, x_m(n-v)]^t$. The

summation in Eq. (5) is taken over all ($=M^J$ patterns) possible length J sequences. The term given by Eq. (6) is the metric for the Viterbi algorithm, and the bias terms in Eq. (5) takes into account the different length of sequences.

It is found from Eqs. (4)-(6) that the knowledge about the channel gain vector $\hat{\mathbf{A}}_{c_j}(n) = z_j(n)\mathbf{a}(\theta_j)$, $0 \leq j \leq v$, is required to calculate the Fano metric. However, this is not known to the receiver. Therefore, instead of using actual $\mathbf{A}_{c_j}(n)$, the receiver estimates $\mathbf{A}_{c_j}(n)$ and uses the estimated vectors $\hat{\mathbf{A}}_{c_j}(n)$ for the Fano metric computation.

3. CHANNEL IDENTIFICATION ALGORITHMS

Three new channel identification algorithms are derived. Algorithm I uses the temporal reference alone. It is assumed that the information symbol sequence is segmented into frames, and that a unique word sequence is periodically embedded as the temporal. Its pattern and timing are known to the receiver. The severe ISI this paper aims to equalize typically happens with very high symbol rate signal transmission. Therefore, the frame length is assumed to be short enough that fading complex envelopes on each propagation path can be regarded as constant over one frame of interest. In this situation, it is reasonable to perform the channel identification only during the unique word period.

Algorithm II and III use both temporal and spatial references. Super resolution techniques such as MUSIC and/or ESPRIT may be used to obtain each path's DOA as the spatial reference.

Algorithm I

Algorithm I estimates the matrix $\mathbf{A}(n)$ by using the unique word sequence. Let $\hat{\mathbf{A}}(n)$ denote the estimate of $\mathbf{A}(n)$ as

$$\hat{\mathbf{A}}(n) = \begin{bmatrix} \hat{\mathbf{A}}_{r_1}(n) \\ \hat{\mathbf{A}}_{r_2}(n) \\ \vdots \\ \hat{\mathbf{A}}_{r_K}(n) \end{bmatrix} = \begin{bmatrix} \hat{\mathbf{A}}_{c_0}(n) & \hat{\mathbf{A}}_{c_1}(n) & \dots & \hat{\mathbf{A}}_{c_v}(n) \end{bmatrix}, \quad (7)$$

where $\hat{\mathbf{A}}_{r_k}(n)$ are the row vectors of $\hat{\mathbf{A}}(n)$. The row vector $\mathbf{A}_{r_k}(n)$ corresponds to the transversal structure of the channel between the transmitter and the k -th element of the antenna array; the j -th element of $\mathbf{A}_{r_k}(n)$ represents the complex envelope of the j -th propagation path. Therefore, $\mathbf{A}_{r_k}(n)$ can be estimated recursively by using the recursive least square (RLS) algorithm as

$$\hat{\mathbf{A}}_{r_k}(n) = \hat{\mathbf{A}}_{r_k}(n-1) + \frac{y_k(n) - \hat{\mathbf{A}}_{r_k}(n-1) \mathbf{x}_T(n)}{\mathbf{x}_T^H(n) \mathbf{P}_k(n-1) \mathbf{x}_T(n) + \lambda} \mathbf{x}_T^H(n) \mathbf{P}_k(n-1) \quad (8)$$

and

$$\mathbf{P}_k(n) = \frac{1}{\lambda} \left[\mathbf{P}_k(n-1) + \frac{\mathbf{P}_k(n-1) \mathbf{x}_T(n) \mathbf{x}_T^H(n) \mathbf{P}_k(n-1)}{\mathbf{x}_T^H(n) \mathbf{P}_k(n-1) \mathbf{x}_T(n) + \lambda} \right] \quad (9)$$

with $\hat{\mathbf{A}}_{r_k}(0) = \mathbf{0}$ and $\mathbf{P}_k(0) = \mathbf{I}_J$, where $\mathbf{P}_k(i) = \langle [\hat{\mathbf{A}}_{r_k}(n) - \mathbf{A}_{r_k}(n)]^H [\hat{\mathbf{A}}_{r_k}(n) - \mathbf{A}_{r_k}(n)] \rangle$ is the error covariance matrix with H denoting the transposed complex conjugate of a matrix. λ is, with $0 < \lambda \leq 1$, the forgetting factor, and \mathbf{I}_J is the $J \times J$ unit matrix. The sequence index m has been deleted from $\mathbf{x}_{Tm}(n)$ in Eq. (9)

because the channel identification process takes place only for the fixed unique word sequence.

Equations (8) and (9) provide a recursive way for estimating $\hat{\mathbf{A}}_{rk}(n)$ element-by-element. However, since

$$\mathbf{P}_k(n) \equiv \mathbf{P}(n) \quad (10)$$

for $1 \leq k \leq K$, the recursive formulas for all antenna elements can be folded into

$$\hat{\mathbf{A}}(n) = \hat{\mathbf{A}}(n-1) + \frac{\mathbf{y}(n) - \hat{\mathbf{A}}(n-1) \mathbf{x}_T(n)}{\mathbf{x}_T^H(n) \mathbf{P}(n-1) \mathbf{x}_T(n) + \lambda} \mathbf{x}_T^H(n) \mathbf{P}(n-1) \quad (11)$$

and

$$\mathbf{P}(n) = \frac{1}{\lambda} \left[\mathbf{P}(n-1) + \frac{\mathbf{P}(n-1) \mathbf{x}_T(n) \mathbf{x}_T^H(n) \mathbf{P}(n-1)}{\mathbf{x}_T^H(n) \mathbf{P}(n-1) \mathbf{x}_T(n) + \lambda} \right] \quad (12)$$

Algorithm II

Algorithm II only estimates one of $\mathbf{A}(n)$'s K row vectors by using Eqs. (8) and (9). Since

$$\mathbf{A}_{rk} = \left[z_0(n) \mathbf{a}_k(\theta_0), z_1(n) \mathbf{a}_k(\theta_1), \dots, z_v(n) \mathbf{a}_k(\theta_v) \right], \quad (13)$$

where $\mathbf{a}_k(\theta)$ is the k -th element of the array response vector $\mathbf{a}(\theta)$ with $\mathbf{a}_k(\theta) \mathbf{a}_k^*(\theta) = 1$, the estimates $\hat{z}_j(n)$ of the fading complex envelopes $z_j(n)$ can be obtained as element-by-element product of

$\hat{\mathbf{A}}_{rk}(n)$ and row vector $[\mathbf{a}_k(\theta_0), \mathbf{a}_k(\theta_1), \dots, \mathbf{a}_k(\theta_v)]^*$. In this process, the knowledge about the DOA's of the J path components is used as the spatial references.

The estimates $\hat{\mathbf{A}}_{cj}(n)$ of matrix $\mathbf{A}(n)$'s column vectors $\mathbf{A}_{cj}(n)$ can then be obtained as

$$\hat{\mathbf{A}}_{cj} = \hat{z}_j(n) \mathbf{a}(\theta_j) \quad \text{for } 0 \leq j \leq v, \quad (14)$$

where the DOA's of the J propagation paths are again used. The estimate matrix $\hat{\mathbf{A}}(n)$ can finally be constructed by arranging $\hat{\mathbf{A}}_{cj}(n)$'s in a column.

Algorithm III

One negative point inherent within Algorithm II is that it only estimates one of $\mathbf{A}(n)$'s K row vectors, resulting in an inaccurate estimate of $\hat{\mathbf{A}}(n)$. By estimating all the K row vectors of $\mathbf{A}(n)$, where Eqs. (11) and (12) are used instead of Eqs. (8) and (9), respectively, and averaging the corresponding estimates $\hat{z}_j(n)$'s of $z_j(n)$'s over $1 \leq k \leq K$, the accuracy can be improved. The remaining part of Algorithm III is the same as Algorithm II.

4. SIMULATION RESULTS

An exhaustive series of computer simulations was conducted to evaluate the overall ISI equalization performance of SSE using an antenna array. Bit error rate (BER) and ERR were evaluated through the simulations. This section presents the performance results for the three channel identification algorithms.

Table 1 summarizes the values of parameters used in the simulations. An equal-power 8-path propagation model ($v=7$) was assumed. The incident angles of the 8 paths were randomly distributed over $0 \leq \theta < 2\pi$. The fading complex envelopes of the paths were kept constant over one frame but the values followed complex Gaussian distribution frame-by-frame. The BER and

ERR results were then averaged over all incident angles and fading envelopes appearing in the simulations.

Figure 2 (A) shows for an eight-element linear array with element spacing of half the wave length the average EER performances of MSA with the three channel identification algorithms. The value of per-path average SNR σ_s^2/σ_g^2 is 9 dB ($=1/8$) lower than per-element average SNR σ^2/σ_g^2 ($=\Gamma$). The ERR curve with Algorithm III is not plotted in Fig. 2 (A) because it is zero for all values of $\Gamma \geq 2$ dB. It is obvious that the accuracy of channel identification is highest with Algorithm III, and lowest accuracy with Algorithm II. A consequence of Fig. 2 (A) is that accurate vector channel estimates do enhance the uniqueness of the MSA sequence estimation using an antenna array.

Figure 2 (B) shows MSA's average BER performances with the three algorithms for the eight-element linear array. The theoretical BER curve, and the curve obtained assuming perfect knowledge about the matrix $\mathbf{A}(n)$ are also plotted. It is found that the BER curves with the three algorithms are worse than the theoretical curve described as the performance upperbound. With perfect knowledge about $\mathbf{A}(n)$, the BER curve is almost parallel to, but is roughly 5 dB worse than the upperbound curve. This indicates that the diversity order supported by the upperbound analysis can be achieved by MSA if perfect channel knowledge is available. Therefore, the 5 dB performance degradation is due to the MSA algorithm used as a low-ERR SSE algorithm.

The tradeoff between complexity and performance is most important in assessing low-ERR SSE algorithms like MSA for ISI equalization. The number of nodes visited by MSA is a reasonable complexity measure. With MLSE, the number of nodes, required to output one symbol, is 2^v for BPSK. Figure 3 shows for an equal-power twelve-path propagation model ($v=11$) as an extreme case, $K=8$, and the memory transfer size $T_A=64$, the per-symbol number N_{vis} of nodes visited by Algorithm I, averaged over all incident angles and fading envelopes appearing in the simulations, versus per-element average SNR Γ . It is found that the N_{vis} value rapidly decreases as Γ increases. This is an advantageous characteristic of MSA over MLSE for which $N_{vis}=2048$ for $v=11$ regardless of the value of the per-element average SNR Γ .

5. CONCLUSIONS

The primary purpose of this paper has been to reduce the erasure probability of SSE algorithms for equalization of multipath fading channels suffering from severe ISI. Exploiting the redundant structure of the composite signal received by multiple elements of an antenna array is the key to enhancing the uniqueness of the sequence estimation by SSE. With a proper use of the MSA algorithm in conjunction with an antenna array, it has been shown that the frame erasure probability can be significantly reduced.

Three new algorithms, Algorithm I, II, and III, were investigated for vector channel identification, the results of which are needed to calculate the Fano metric for SSE. Algorithm I uses a temporal reference alone. The array response vectors for the multiple propagation paths are estimated by using unique word sequences transmitted as the temporal reference. Algorithms II and III use both temporal and spatial references, assuming that the spatial reference is available as a result of a spatial signal structure analysis.

Results of computer simulations conducted to reveal the sensitivity of the performance to channel estimation accuracy have been presented. ERR and BER performances with the three algorithms were evaluated and the results were compared. With perfect knowledge about the vector channel, MSA's BER curve

was found to be almost parallel to the upperbound curve. This indicates that the diversity order supported by the upperbound analysis can be achieved by MSA if perfect channel knowledge is available. It was shown that Algorithm III can significantly improve the ERR performance over the other two algorithms. MSA's ERR/BER tradeoff observed in the performance curves was found quite optimistic: ERR can be significantly reduced by Algorithm III while the increase in BER is relatively minor.

The complexity of MSA with an antenna array was also investigated. It was shown that even under the twelve-path propagation environment, the number of the nodes visited to output one symbol, rapidly decreases as per-element average SNR increases for MSA with Algorithm I.

References

[1] A. Duel-Hallen and C. Heegard, "Delayed Decision Feedback Sequence Estimation", IEEE Trans. COM., Vol. COM-37, pp. 428-436, 1989

[2] S. Ariyavisitakul and L.J. Greenstein, "Reduced-Complexity Equalization Techniques for Broadband Wireless Channels", IEEE JSAC., Vol. SAC-15, No. 1, 1997
 [3] F. Xiong, A. Zerik and E. Shwedyk, "Sequential Sequence Estimation for Channels with Intersymbol Interference of Finite or Infinite Length", IEEE Trans. COM., Vol. COM-38, pp. 795-804, 1990
 [4] E. Katz and G.L. Stuber, "Sequential Sequence Estimation for Trellis-Coded Modulation on Multipath Fading ISI Channels", IEEE Trans. COM., Vol. COM-43, pp. 2882-2885, 1995
 [5] P. Chevillat and D.J. Costello, Jr., "A Multiple Stack Algorithm for Erasure-free Decoding of Convolutional Codes", IEEE Trans. COM., Vol. COM-25, pp. 1460-1470, 1977
 [6] H.H. Ma, "The Multiple Stack Algorithm Implemented on a Zilog Z-80 Microcomputer", IEEE Trans. COM., Vol. COM-28, pp. 1876-1882, 1980

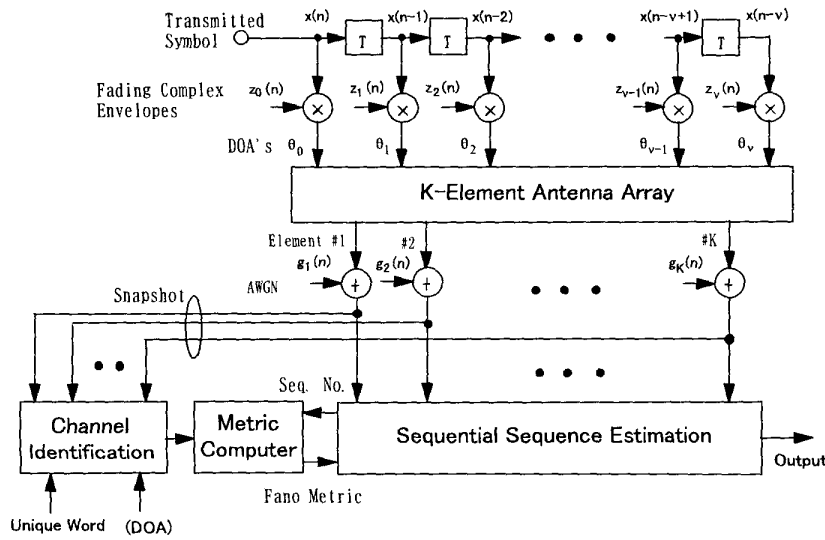


Fig. 1 System Block Diagram

Modulation	BPSK
Unique Word Length	31 Symbols
Information Length	128 Symbols
Normalized Maximum Doppler Frequency	$f_D T$ (Very Slow)
Stack Size	MA 256
Number of Stack	NA 16
Transfer Size	TA 64
Maximum Memory Size (Computational Limit)	LA 4096

Table 1 Parameter Values for Simulation

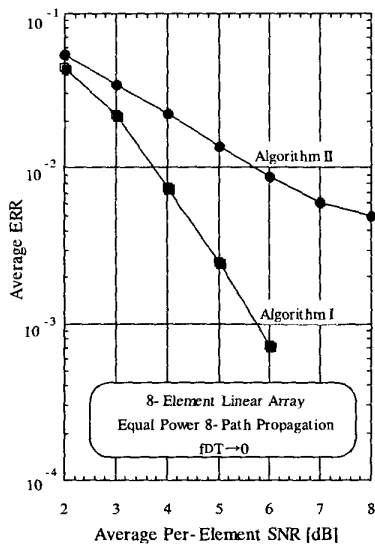


Fig. 2 (A) Average ERR Performance

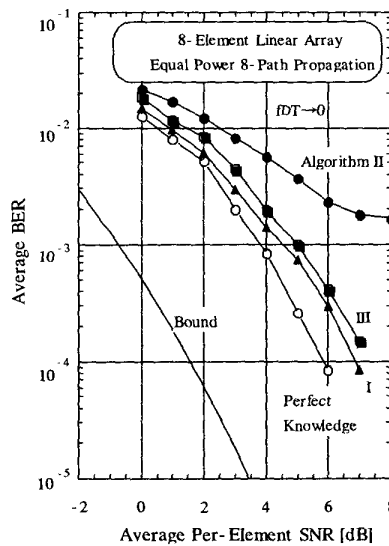


Fig. 2 (B) Average BRR Performance

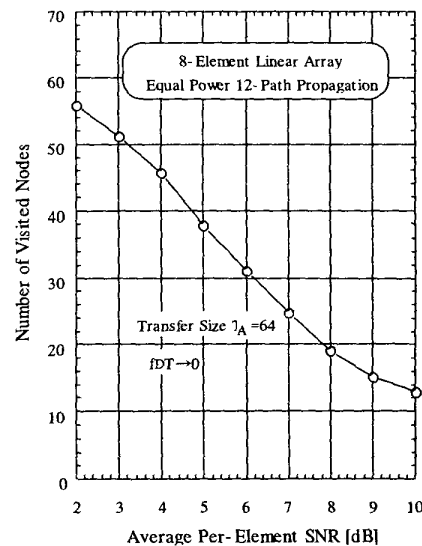


Fig. 3 Average Number of Nodes Visited