Channel Identification and Sequential Sequence Estimation Using Antenna Array for Broad-Band Mobile Communications

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***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 intersymbol interference (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 then presented to compare the performances of the three algorithms for vector channel identification. The propagation scenario assumed in the simulations is equal-power 12-path propagation, in which, even with binary phase shift keying (BPSK), maximum likelihood sequence estimation (MLSE) requires 2048 states. It is shown that even in such a complicated situation, the MSA algorithm can achieve excellent ERR and BER performances with reasonable computational complexity.**

***Index Terms*—Antenna array, channel estimation, mobile communication, sequence estimation.**

I. INTRODUCTION

INTERSYMBOL 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.

Several excellent ideas have been proposed to reduce the time-variant ISI effects with the aim of achieving broad-band and reliable signal transmission capability [1]–[7]. Maximum likelihood sequence estimation (MLSE) with adaptive multipath channel identification [1]–[3] has been considered most effective in reducing the effects of ISI caused by relatively small, say, two–three symbols long, channel memory length ν. However, since the computational complexity of the Viterbi algorithm for MLSE grows exponentially with the channel memory length, the practical complexity limit is likely to be exceeded when MLSE-based equalizers are used in mobile multimedia communications applications. This is because channel memory size increases with the signal bandwidth, i.e., more than ten symbols for ten Msymbols/s transmission.

Delayed decision feedback sequence estimation (DDFSE) proposed by [4] and [5] is based on the combined use of MLSE and the decision feedback equalizer (DFE). The computational complexity of DDFSE is dominated by the MLSE part since the complexity of DFE is merely proportional to the channel memory length. 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 which is sometimes referred to as the "DFE penalty." The DDFSE equalizer suffers from the DFE penalty if the channel delay spread falls into a range which cannot be equalized by MLSE alone.

The potential of the sequential sequence estimation (SSE) technique for ISI equalization was indicated in [6] and [7], where complex envelopes with the multiple propagation paths were assumed to be known. The computational effort needed for the sequential search process is almost independent of the channel memory length. 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.

The SSE algorithm was originally developed for decoding convolutional codes with very large constraint length J $(=\nu + 1)$, for which the Viterbi decoder's complexity far exceeded the practical limit [8], [9]. Various aspects have been examined in terms of the asymptotic and practical performance of SSE algorithms. Theoretically, SSE performance is asymptotically equivalent to that of MLSE if unlimited computation capability is available. However, reality does not allow unlimited computations in decoding large K convolutional codes: 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 [10], [11] may be used, which, instead of trying full search, output tentative decisions if buffer overflow happens, and, hence, lower erasure rates (ERR's) are achieved.

Manuscript received January 19, 1998; revised November 2, 1998.

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Publisher Item Identifier S 0018-9545(00)03679-3.

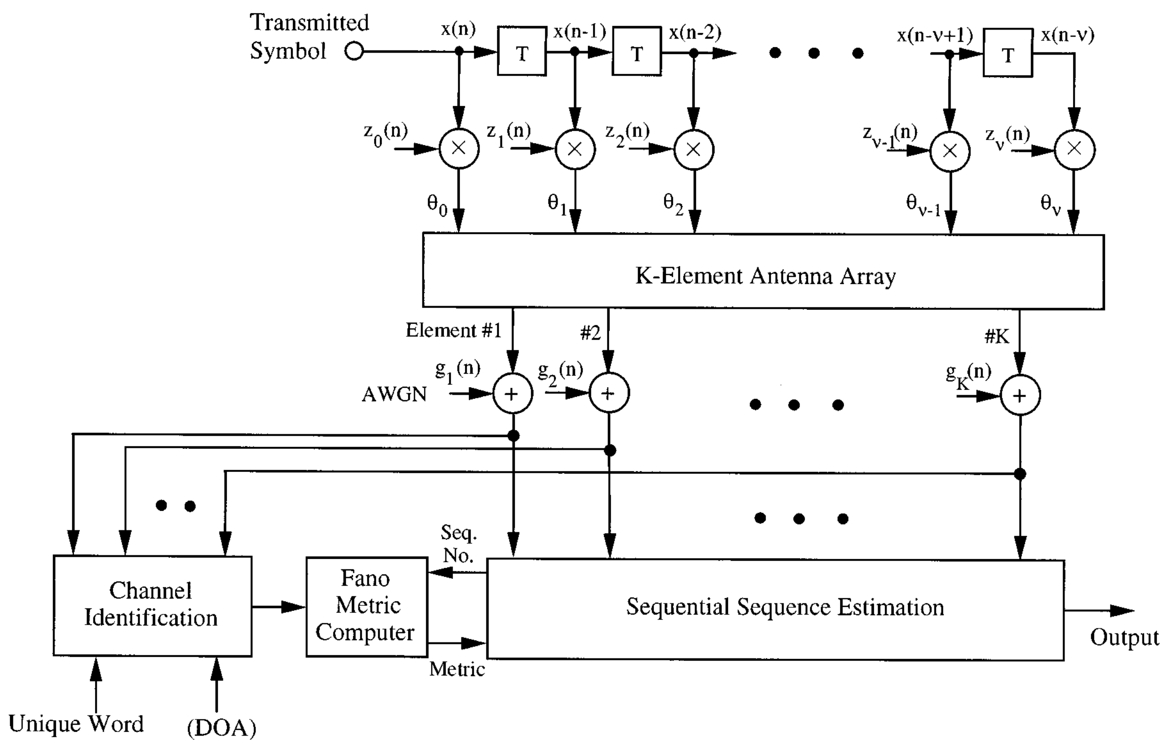


Fig. 1. System block diagram.

One major difference between the decoding of convolutional codes and the adaptive equalization of ISI, both using the SSE technique, is that the channel is assumed to be fixed in the former case whereas it is time variant in the latter. 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 $\nu+1$ 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-arrivals (DOA's) of each path component is assumed to be available as the spatial reference. The Fano metric [8], which is used to make a reliability comparison among candidate sequences with different lengths in SSE, is then calculated based upon the result of the vector channel identification.

This paper is organized as follows. Section II shows the system model used in this paper and describes mathematical expressions for each component of the model. Section III describes details of the three channel identification algorithms investigated in this paper. Section IV derives an upperbound of the symbol error rate of the SSE-based equalizers assuming the use of an antenna array. Section V presents results of computer simulations conducted for the binary phase shift keying (BPSK) to evaluate the ISI equalization performance of the three algorithms where the multiple stack algorithm (MSA) is used as a low ERR SSE scheme.

II. System Model

A. Channel

Fig. 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 [6] and [7], where the transversal filter has $\nu+1$ $(=J)$ 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

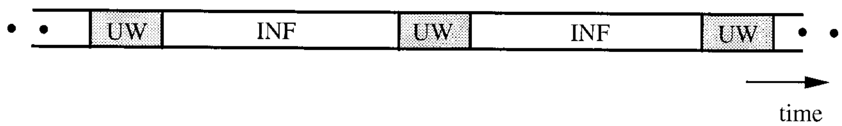


Fig. 2. Frame format.

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

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

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

$$\mathbf{r}(n) = \sum_{j=0}^{\nu} \mathbf{a}(\theta_j) \cdot z_j(n) x(n-j) \tag{2}$$

is the antenna array output vector in the absence of noise, $J = \nu + 1$ is the number of the propagation path, θ_j is the jth 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 jth 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 jth path's average power and $\Gamma = \sigma^2/\sigma_g^2$ is, with $\sigma^2 = \sigma_0^2 + \sigma_1^2 + \ldots + \sigma_\nu^2$, the per-element average received signal-to-noise power ratio (SNR).

B. Receiver

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

$$\mathbf{A}(n) = [\mathbf{A}_{c0}(n) \quad \mathbf{A}_{c1}(n) \quad \ldots \quad \mathbf{A}_{c\nu}(n)] = \begin{bmatrix} \mathbf{A}_{r1}(n) \\ \mathbf{A}_{r2}(n) \\ \vdots \\ \mathbf{A}_{rk}(n) \end{bmatrix} \tag{3}$$

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

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

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

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

with

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

where $\mathbf{x}_{Tm}(n)$ is the vector comprised of the mth sequence's last J entries, i.e., $\mathbf{x}_{Tm}(n) = [x_m(n), x_m(n-1), \ldots, x_m(n-\nu)]^t$. The summation in (5) is taken over all ($=M^J$ patterns) possible length J sequences. The term given by (6) is the metric for the Viterbi algorithm, and the bias terms in (5) take into account the different length of sequences.

It is found from (4) to (6) that the knowledge about the channel gain vector $\mathbf{A}_{cj}(n) = z_j(n)\mathbf{a}(\theta_j)$, $0 \le j \le \nu$ is required to calculate the Fano metric. However, this is not known to the receiver. Therefore, instead of using actual $\mathbf{A}_{cj}(n)$, the receiver estimates $\mathbf{A}_{cj}(n)$ and uses the estimated vectors $\hat{\mathbf{A}}_{cj}(n)$ for the Fano metric computation. Section III describes three algorithms for obtaining $\hat{\mathbf{A}}_{cj}(n)$ using temporal and/or spatial references.

III. Channel Identification Algorithms

Three new channel identification algorithms are derived in this paper. Algorithm I uses the temporal reference alone. As shown in Fig. 2, the information symbol sequence is segmented into frames. A unique word sequence is periodically embedded as the temporal reference in each frame to be transmitted. 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.

Algorithms II and III use both temporal and spatial references. Super-resolution techniques such as MUSIC [12] and ESPRIT [13] may be used to obtain each path's DOA as the spatial reference, but the techniques themselves and their performances exceed the scope of this paper.

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

$$\hat{\mathbf{A}}(n) = [\hat{\mathbf{A}}_{c0}(n)\hat{\mathbf{A}}_{c1}(n)\dots\hat{\mathbf{A}}_{c\nu}(n)] = \begin{bmatrix} \hat{\mathbf{A}}_{r1}(n) \\ \hat{\mathbf{A}}_{r2}(n) \\ \vdots \\ \hat{\mathbf{A}}_{rk}(n) \end{bmatrix} \tag{7}$$

where $\hat{\mathbf{A}}_{rk}(n)$ are the row vectors of $\hat{\mathbf{A}}(n)$. The row vector $\mathbf{A}_{rk}(n)$ corresponds to the transversal structure of the channel between the transmitter and the kth element of the antenna array: the jth element of $\mathbf{A}_{rk}(n)$ represents the complex envelope of the jth propagation path. Therefore, $\mathbf{A}_{rk}(n)$ can be estimated recursively by using the recursive least square (RLS) algorithm [14] as

$$\hat{\mathbf{A}}_{rk}(n) = \hat{\mathbf{A}}_{rk}(n-1) + \frac{[\mathbf{y}k(n) - \hat{\mathbf{A}}_{rk}(n-1)\mathbf{x}_T(n)]}{\mathbf{x}_T(n)^H\mathbf{P}_k(n-1)\mathbf{x}_T(n)+\lambda} \cdot \mathbf{x}_T(n)^H\mathbf{P}_k(n-1) \tag{8}$$

and

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

with $\hat{\mathbf{A}}_{rk}(0) = \mathbf{0}$ and $\mathbf{P}_k(0) = \mathbf{I}_J$, where $\mathbf{P}_k(i) = \langle[\hat{\mathbf{A}}_{rk}(n) - \mathbf{A}_{rk}(n)]^H[\hat{\mathbf{A}}_{rk}(n) - \mathbf{A}_{rk}(n)]\rangle$ 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 (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 $\mathbf{A}_{rk}(n)$ element by element. However, since

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

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

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

and

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

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

$$\mathbf{A}_{rk}(n) = [z_0(n)a_k(\theta_0) \quad z_1(n)a_k(\theta_1) \quad \dots \quad z_\nu(n)a_k(\theta_\nu)] \tag{13}$$

where $a_k(\theta)$ is the kth element of the array response vector $\mathbf{a}(\theta)$ with $a_k(\theta)a_k^*(\theta) = 1$, 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 $[a_k(\theta_0), a_k(\theta_1), \dots, a_k(\theta_\nu)]^*$. 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

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

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 (11) and (12) are used instead of (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.

IV. Performance Estimation

As described in the Introduction, the SSE performance is asymptotically equivalent to that of an MLSE. Hence, it is reasonable to predict SSE performances by using their corresponding MLSE performance figures. It is well known that in the presence of multipath, MLSE combines all the multipath components, which results in diversity improvement. Theoretically, the received signal components are cophased and combined by MLSE, which is equivalent to maximum ratio combining (MRC).

The performance upperbound of SSE using an antenna array can be predicted by assuming that not only the received signal components corresponding to each propagation path, but also those received by each antenna element can be cophased and combined. The latter does contribute to increasing the energy of the combined signal by an amount corresponding to the number of the antenna elements, but does not contribute to increasing the diversity order. This is because the antenna elements are located close enough in space so that (2) holds: only the phases of signals received by other elements differ from each other.

The values of the path components' average powers depend on the delay profile. The average symbol error probability P_s for MRC combining of signals having different average powers can be theoretically derived through the characteristic function approach [15]. The theoretical curve for the special case where all the path components have the same average power can be obtained as

$$P_s = \int_0^\infty p_s(\gamma) \cdot \frac{K}{(J-1)!}\frac{(\gamma K)^{J-1}}{(\Gamma/J)^J}\exp(-\gamma KJ/\Gamma)\,d\gamma \tag{15}$$

where $p_s(\gamma)$ is the symbol error probability of the modulation scheme used for the *instantaneous* SNR γ. For BPSK, which is

TABLE I
VALUES OF PARAMETERS

Stack Size	M_A	256
Number of Stack	N_A	16
Transfer Size	T_A	64
Maximum Memory Size (Computational Limit)	L_A	4096
Modulation		BPSK
Unique Word Length		31 Symbols
Information Length		128 Symbols

used in the simulations described in the next section, (15) can be calculated as [16]

$$P_s = \left(\frac{1-\mu}{2}\right)^J \sum_{j=0}^{J-1} \binom{J-1+j}{j} \left(\frac{1+\mu}{2}\right)^j \tag{16}$$

with

$$\mu = \sqrt{\frac{K\Gamma/J}{1+K\Gamma/J}}. \tag{17}$$

V. 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.

BPSK was used as the modulation scheme. Information and unique word sequences were, respectively, 128 and 31 symbols long, resulting in 159 symbols in total. The multiple stack algorithm (MSA) [10], [11] was used as a low ERR SSE algorithm. The key parameters of the MSA algorithm are the number N_A of the stack memories and their size M_A, the memory transfer size T_A, and the maximum memory size L_A $(=N_A \times M_A)$ representing the computational limit corresponding to acceptable delay. Table I summarizes the values of parameters used in the simulations.

The first simulation was conducted for an equal-power eight-path propagation model $(\nu = 7)$. The incident angles of the eight 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 Gausian distribution frame by frame. This situation corresponds to that in which the frame length is very short compared to the maximum Doppler fading frequency f_D. The BER and ERR results were then averaged over all incident angles and fading envelopes appearing in the simulations.

Fig. 3(a) shows for an eight-element linear array with element spacing of half the wavelength the average EER performances of MSA with the three channel identification algorithms. The value of per-path average SNR σ_j^2/σ_g^2 is 9 dB $(=1/8)$ lower than per-element average SNR σ^2/σ_g^2 $(=\Gamma)$ in this case. The ERR curve with Algorithm III is not plotted in Fig. 3(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. 3(a) is that accurate vector channel estimates do enhance the uniqueness of the MSA sequence estimation using an antenna array.

Fig. 3(b) shows MSAs average BER performances with the three algorithms for the eight-element linear array. The theoretical BER curve given by (16) and (17) and the curve obtained assuming perfect knowledge about the matrix $\mathbf{A}(n)$ are also plotted in the figure. 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.

In fact, MSA transfers the T_A most reliable sequence candidates if the stack memory being used becomes full. Therefore, it is likely that the frame end is reached and the corresponding candidate sequence is stored as a temporary decision result. It is output if the time given for sequence search expires. This operation of MSA is, with the use of antenna array, effective in reducing ERR, which is, however, at a sacrifice of the increased possibility of worsening BER performance since the most likely sequence might not have been transferred. The BER curve with Algorithm III is found slightly worse than Algorithm I, even though Algorithm III's ERR is zero for $\Gamma \geq 2$ dB. This is because of the ERR/BER tradeoff inherent within MSA.

Fig. 3(c) compares the average BER and ERR performances of MSA with those of the single stack algorithm (SSA). Algorithm I was used for the channel identification, and the values of the parameters related to the propagation model and antenna geometry were the same as those used in Fig. 3(a) and (b). For SSA, the stack size was assumed to be 4096, which is equal to the value of $N_A \times M_A (= 256 \times 16)$ for MSA. It is found that with a slight increase in BER, MSA can significantly reduce ERR.

Fig. 4(a) and (b) shows for an equal-power 12-path propagation model $(\nu = 11)$ as an extreme case average BER and ERR performances, respectively, of Algorithm I with the number K of antenna elements as a parameter. It is found that smaller ERR and BER can be achieved by increasing the number of antenna elements. This is because it is more unlikely with larger K that sequence estimation uniqueness fails at all antenna elements. With $K \geq 6$, BER $>$ ERR for $\Gamma \geq 6$ dB, and, hence, the effect of frame erasure on ISI equalization performance can be made negligible.

It is found from a comparison of Figs. 3(b) and 4(a) that the average BER performance is better with $J = 8$ than with

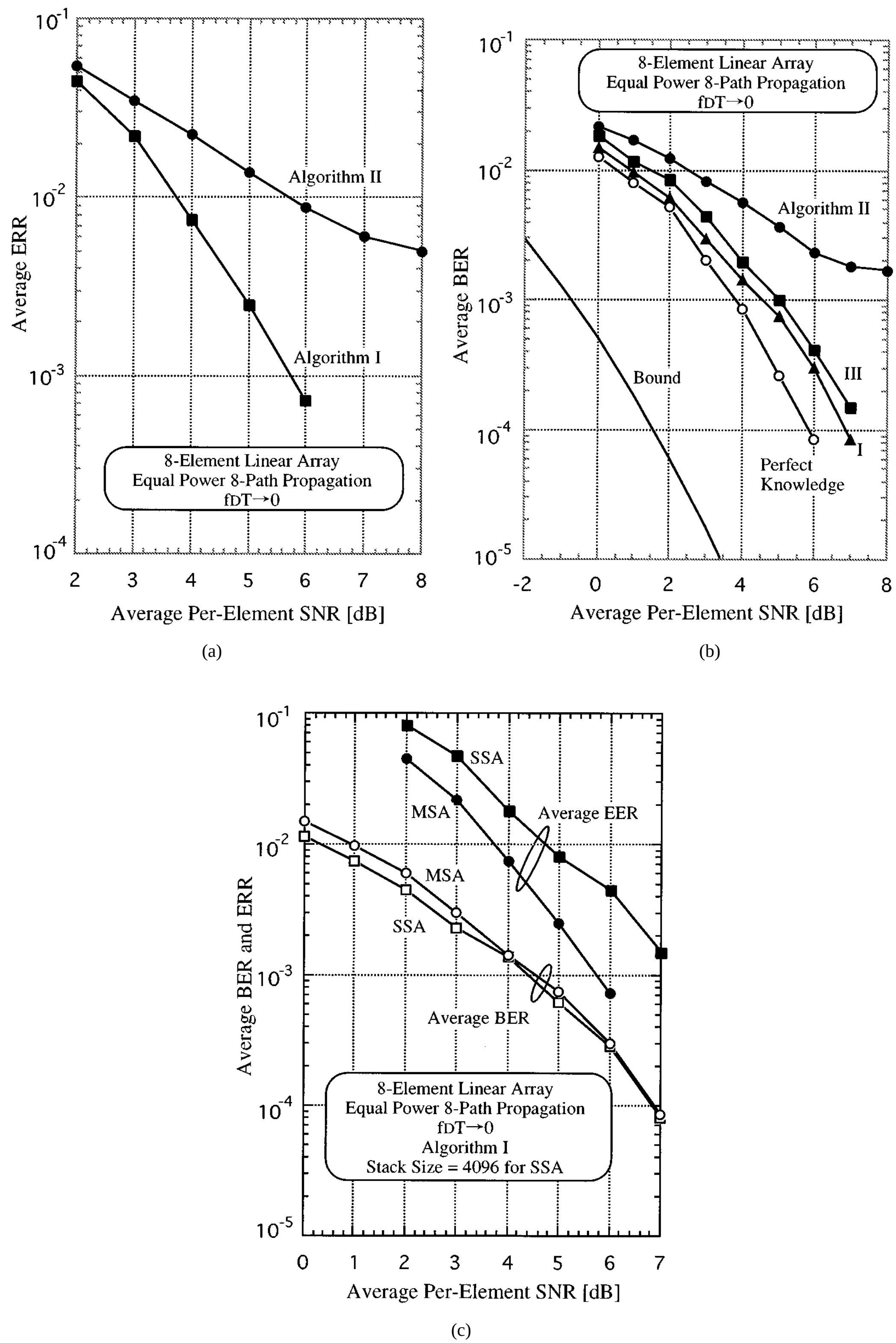
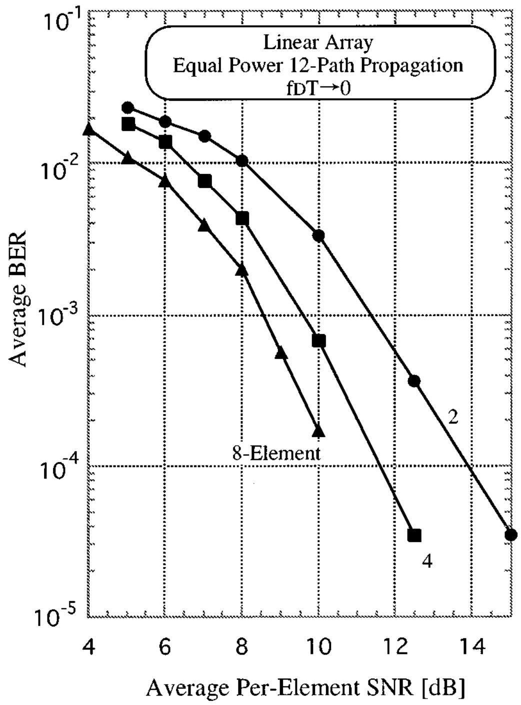


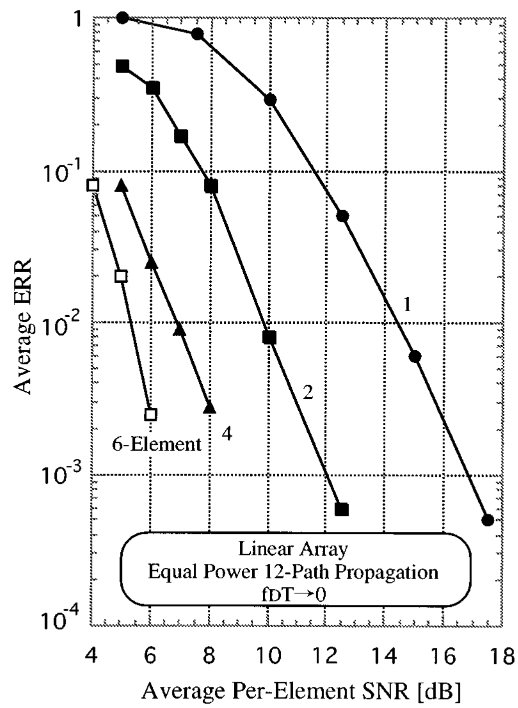
Fig. 3. (a) Average ERR performance with $K = 8$ and $J = 8$. (b) Average BER performance with $K = 8$ and $J = 8$. (c) Average BER and ERR performances of MSA and SSA with $K = 8$ and $J = 8$.

$J = 12$. This is not a surprising result, considering that the per-path average SNR with $J = 12$ is lower than with $J = 8$. In both cases, the unique word sequence was 31 symbols long, with which the channel estimates with $J = 12$ are relatively unreliable compared with with $J = 8$. In this situation, a lot of "back and forth" takes place in the MSA sequence search, so temporary decision output is common.

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 rea-



(a)



(b)

Fig. 4. (a) Average BER performance with $K = 8$ and $J = 12$. (b) Average ERR performance with $K = 8$ and $J = 12$.

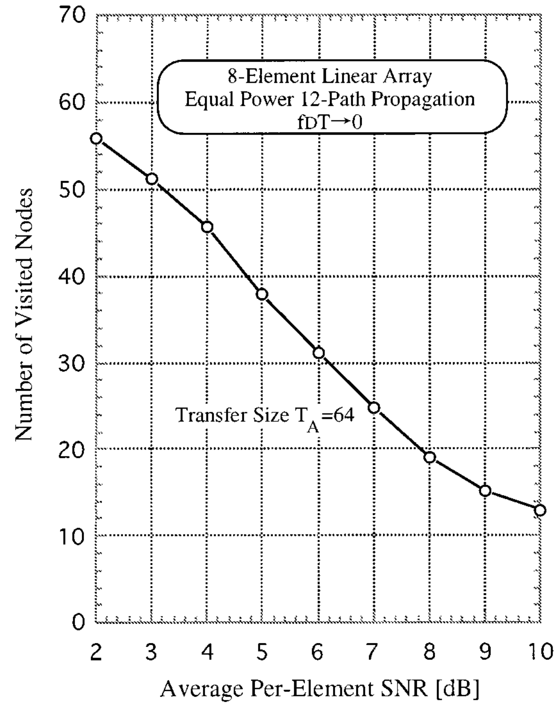


Fig. 5. Average number of nodes visited by MSA with $K = 8$ and $J = 12$.

sonable complexity measure. With MLSE, the number of nodes, required to output one symbol, is 2^ν for BPSK. Fig. 5 shows for $J = 12$, $K = 8$, and the memory transfer size $T_A = 64$, the per-symbol number $N_{\rm vis}$ 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 $N_{\rm vis}$ value rapidly decreases as Γ increases. This is an advantageous characteristic of MSA over MLSE for which $N_{\rm vis} = 2048$ for $\nu = 11$ regardless of the value of the per-element average SNR Γ.

VI. CONCLUSION

The primary purpose of this paper was 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–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. Since the signal structure analysis is rendered unreliable in multipath mobile communication environments, the first algorithm is most promising from a practical implementation viewpoint. However, it is interesting to know how the spatial reference can help the channel identification improve its accuracy, which motivated the examination of Algorithm II and III performances.

An exhaustive series of computer simulations was conducted to reveal the sensitivity of the performance to channel estimation accuracy. 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. Under an equal-power 12-path propagation environment, selected in the simulations as an extreme case, Algorithm I can achieve BER smaller than ERR if per-element average SNR is larger than 6 dB and there are more than six antenna elements.

The complexity of MSA with an antenna array was also evaluated in terms of the number of the nodes visited by the MSA sequence search. It was shown that even under the 12-path propagation environment, the number of the nodes visited to output one symbol rapidly decreases as the per-element average SNR increases for MSA with Algorithm I. This is a great advantage of MSA over MLSE for which the number is constant $(N_{\text{vis}} = 2^{11})$ regardless of the channel condition.

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