Column-Anchored Zeroforcing Blind Equalization for Multiuser Wireless FIR Channels

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***Abstract*—We propose a direct blind zeroforcing approach to cancel intersymbol interference (ISI) in multiple user finite impulse response (FIR) channels. By selectively anchoring columns of the channel convolution matrix, we present two column-anchored zeroforcing equalizers (CAZE), one without output delay and one with a chosen delay. Unlike many known blind identification algorithms, these equalizers do not need an accurate estimate of the channel orders. Exploiting second-order statistics (SOS) of the received signals, they can retain preselected d columns in the channel convolution matrix (d is the number of users) and force the remaining columns to zero. CAZE can effectively equalize single-input–multiple-output (SIMO) systems and can reduce dynamic multiple-input–multiple-output (MIMO) systems into a memoryless signal mixing system for source separation. Simulation results show that the CAZE is not only effective for blind equalization of linear quadrature amplitude modulation (QAM) systems, but it is also applicable to the nonlinear GMSK modulation in the popular wireless GSM systems when computational cost severely limits the use of nonlinear methods such as the Viterbi algorithm.**

***Index Terms*—Blind equalization, digital wireless communications, GSM systems, multiuser systems.**

I. Introduction

BLIND equalization has been one of the most active areas of research in recent years. The potential application of blind equalization in wireless communication is one of the main reasons for its popularity. Although initial studies of blind equalization were focused on single-user systems, cochannel interference (CCI) typically arises in wireless systems and has generated a great deal of research interest in the blind equalization of multiple-input–multiple-output (MIMO) systems.

Blind equalization typically relies on both higher order statistics (HOS) and second-order statistics (SOS) of channel output signals. The paper by Tong *et al.* [1] provided a successful blind equalizer based only on SOS for single-input–multiple-output (SIMO) systems. Since then, a number of SOS-based algorithms have been developed to rely on the SIMO system model in which the multiple output channels must be diverse enough to share no common zeros [2]–[4], [6], [7], [9]–[12]. Many of these SIMO algorithms can be generalized to MIMO systems so long as the number of virtual users is smaller than the number of virtual outputs [13].

SOS methods require that channel diversity be available in terms of additional antennas or from oversampling output signals of channels with excess bandwidth. Clearly, all SOS-based algorithms rely critically on channel diversity. If there are common (or near common) zeros among diversity channels, blind channel identification is no longer possible from SOS alone, and HOS can be used to compensate the loss of information.

Another major drawback of many existing SOS methods is the fact that many tend to be sensitive to channel order estimate. When channel order is unknown, accurate channel order estimate is difficult to achieve and poor blind channel identification results are common. Another feature common to many existing blind algorithms is that they must first perform blind channel identification [1], [9], [13]. Although channel estimates are essential to nonlinear equalizers such as the Viterbi sequence estimator, linear equalizers based on blind channel estimate do not always perform well since channel estimation errors tend to be magnified by linear equalizers.

In this paper, our goal is to develop an SOS blind equalization approach that is less sensitive to channel order estimates and directly equalize the channel without channel identification. We shall focus on SOS methods that can be applied to MIMO systems for direct linear equalization. Our goal is to develop a direct blind equalization approach that is less sensitive to channel order estimation. The fact that many existing methods first estimate the channel response and then design the equalizer makes them more sensitive to channel order estimate. For a system with d inputs, our new approach can cancel all intersymbol interference (ISI) while retaining (anchoring) the d preselected columns of channel convolution matrix. These column-anchored zeroforcing equalizers (CAZE) can thus equalize both SIMO systems and MIMO systems. Their implementation is quite simple and efficient.

The paper is organized as follows. In Section II, the problem of blind equalization for MIMO systems is formulated. In Section III, the concept of CAZE for blind ISI cancellation is developed. Several different algorithms based on the CAZE concept are presented in Section IV. Finally, simulation examples of CAZE are given for a standard QAM linear modulation systems and for the GSM wireless system.

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II. Problem Formulation

Consider a linear discrete MIMO system with d user inputs and N outputs derived from multiple antennae and oversampling. Denote the symbol sequence from the jth user as $\{\alpha_j(k)\}$. Denote the input signal vector

$$\boldsymbol{\alpha}(n) = [\alpha_1(n), \alpha_2(n), \ldots, \alpha_d(n)]^T$$

where superscript T represents matrix transpose. We also denote $\dagger$ as the conjugate transpose operator. Let the linear dynamic channel be modeled by an Mth order finite impulse response (FIR) system so that the sampled channel output signal is an $N \times 1$ vector

$$\boldsymbol{y}(n) = \sum_{k=0}^{M} \boldsymbol{H}(k)\boldsymbol{\alpha}(n-k) + \boldsymbol{w}(n)$$

where $\boldsymbol{H}(k)$ is an $N \times d$ channel response matrix and $\boldsymbol{w}(n)$ is an $N \times 1$, independently identically distributed (i.i.d.) noise vector.

To simplify algorithm derivation, we first assume zero noise $\boldsymbol{w}(n) = 0$. Clearly, the channel response $\{\boldsymbol{H}(k)\}$ in general contains both ISI and CCI. When all $\boldsymbol{H}(k)$ are zeros except for one k, $\boldsymbol{y}(n)$ has zero ISI. Let

$$\boldsymbol{s}(m) = \left[\boldsymbol{\alpha}(m)^T, \boldsymbol{\alpha}(m-1)^T, \ldots, \boldsymbol{\alpha}(m-L-M)^T\right]^T$$
$$\boldsymbol{o}(m) = \left[\boldsymbol{y}(m)^T, \boldsymbol{y}(m-1)^T, \ldots, \boldsymbol{y}(m-L)^T\right]^T$$
$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{H}(0) & \boldsymbol{H}(1) & \cdots & \boldsymbol{H}(M) & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \boldsymbol{H}(0) & \boldsymbol{H}(1) & \cdots & \boldsymbol{H}(M) & \ddots & \mathbf{0} \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{0} & \boldsymbol{H}(0) & \boldsymbol{H}(1) & \cdots & \boldsymbol{H}(M) \end{bmatrix}. \quad (1)$$

The vector of $L+1$ baud output signals can be given as

$$\boldsymbol{o}(m) = \boldsymbol{A}\boldsymbol{s}(m). \quad (2)$$

Let $M' = M + L + 1$. $\boldsymbol{A}$ is an $N(L+1) \times dM'$ generalized Sylvester matrix and is called "channel convolution matrix." Observe that $\boldsymbol{H}(i)$ has d columns. We refer to every group of d columns belonging to an $\boldsymbol{H}(i)$ in $\boldsymbol{A}$ as a block column and $\boldsymbol{A}$ thus has M' block columns.

Blind equalization needs to recover $\boldsymbol{s}(m)$ from $\boldsymbol{o}(m)$ without any explicit knowledge of $\boldsymbol{A}$ and $\boldsymbol{s}(m)$. Only the structure of $\boldsymbol{A}$ and the statistics of $\boldsymbol{s}(m)$ are known. In this paper, we focus on the development of linear blind equalizers because of their simplicity. It should be noted, however, that when sufficient computation power is available, nonlinear methods such as the Viterbi algorithm will always provide superior performance.

For linear equalization, denote $\boldsymbol{G}$ as the matrix operating as an equalizer. The equalizer output is generated from

$$\boldsymbol{e}(m) \triangleq \boldsymbol{G}\boldsymbol{o}(m) = \boldsymbol{G}\boldsymbol{A}\boldsymbol{s}(m).$$

ISI zeroforcing in MIMO systems is to force all entries in $\boldsymbol{GA}$ to zero except for one block column.

Without loss of generality, we can define user indexes such that $\boldsymbol{H}(0)$ does not have all-zero columns. We shall rely on the use of SOS of the received signal $\boldsymbol{o}(m)$. As in many methods based on SOS, we assume that the channel convolution matrix $\boldsymbol{A}$ has full column rank after removing all zero columns (i.e., $\boldsymbol{H}$ is irreducible and column reduced) [7]. This implies that all nonzero columns of $\boldsymbol{A}$ are linearly independent. If there are indeed all zero columns, then their corresponding input signal symbol is missing from $\boldsymbol{o}(m)$. Therefore they cannot be recovered. Typically, when source signals do not span the same delays, there are all zero columns in $\boldsymbol{H}(k)$. Our assumption allows our algorithms to be applicable to these scenarios. Note that if this assumption is not satisfied, one may resort to HOS approaches.

One necessary condition for the selection of L is that $\boldsymbol{A}$ should have more rows than columns. It is therefore essential that $N > d$. Furthermore, we assume that all user symbol sequences are uncorrelated with unit variance without loss of generality. It is then apparent that

$$E\{\boldsymbol{s}(m+k)\boldsymbol{s}(m)^\dagger\} = \boldsymbol{J}^{kd} \quad (3)$$

where $E\{\cdot\}$ is the expectation operator and $\boldsymbol{J}$ denotes the Jordan matrix whose first subdiagonal entries below the main diagonal are unity while all remaining entries are zeros. We also use notations

$$\boldsymbol{J}^0 = \boldsymbol{I} \quad \text{and} \quad \boldsymbol{J}^{-1} = \boldsymbol{J}^\dagger. \quad (4)$$

III. Column Anchoring

A. Useful Definitions and Column Shifting

A system matrix is said to be ISI free if it has only one nonzero block column. To remove ISI in $\boldsymbol{o}(m)$, one possible thought is to design a matrix $\boldsymbol{G}$ so that the matrix $\boldsymbol{D} = \boldsymbol{GA}$ becomes an ISI-free matrix.

Applying (2), the auto-covariance matrix of the received signal vector is

$$\boldsymbol{R}(k) = E\{\boldsymbol{o}(m+k)\boldsymbol{o}(m)^\dagger\} = \boldsymbol{A}\boldsymbol{J}^{kd}\boldsymbol{A}^\dagger, \quad \text{for } k = \ldots, -2, -1, 0, 1, 2, \ldots. \quad (5)$$

Denote superscript # as the pseudoinverse operator. Then for $\boldsymbol{A}$ with full rank (column reduced), we have

$$\boldsymbol{A}^\dagger(\boldsymbol{A}\boldsymbol{A}^\dagger)^{\#}\boldsymbol{A} = \boldsymbol{I}_A \quad (6)$$

where $\boldsymbol{I}_A$ is an identity matrix except with all zero rows corresponding to the all zero columns of $\boldsymbol{A}$. Notice that due to the corresponding zero columns of $\boldsymbol{A}$ and the zero rows of $\boldsymbol{I}_A$

$$\boldsymbol{A}\boldsymbol{I}_A = \boldsymbol{A}. \quad (7)$$

The following important observations must be made.

- Because of the structure of the matrix $\boldsymbol{A}$ in (1), $\boldsymbol{H}(0)$ must be full rank as all its columns are nonzero.
- Since $\boldsymbol{H}(0)$ is full rank, all zero columns can only appear among the last M block (or Md) columns.
- Among the last Md columns, all nonzero elements in the $k+d$th column are shared by the kth column. Hence if the k_zth column is all zero, so is $k_z + d$th column.

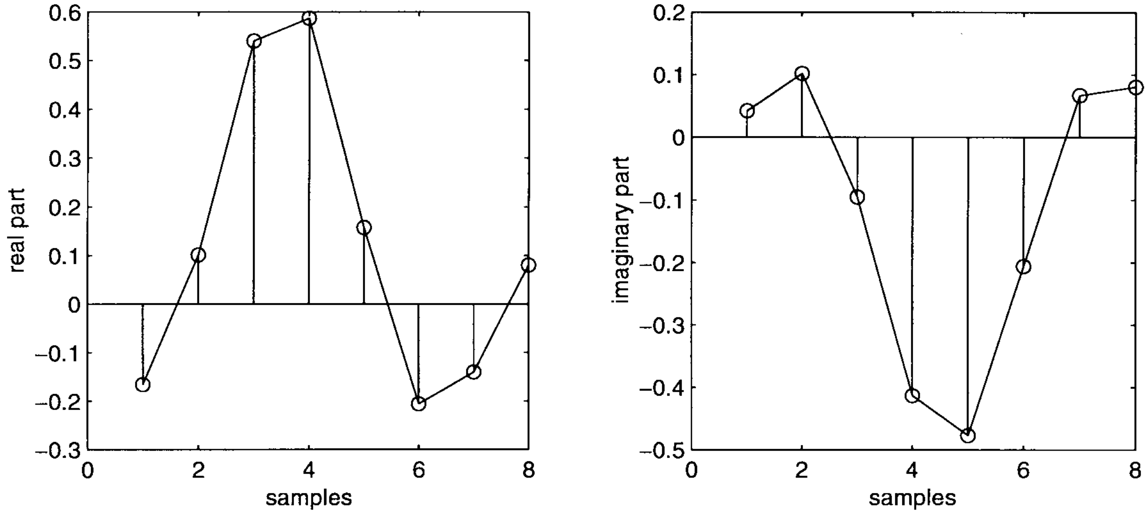


Fig. 1. Real and imaginary parts of the channel $h(t)$ before CAZE.

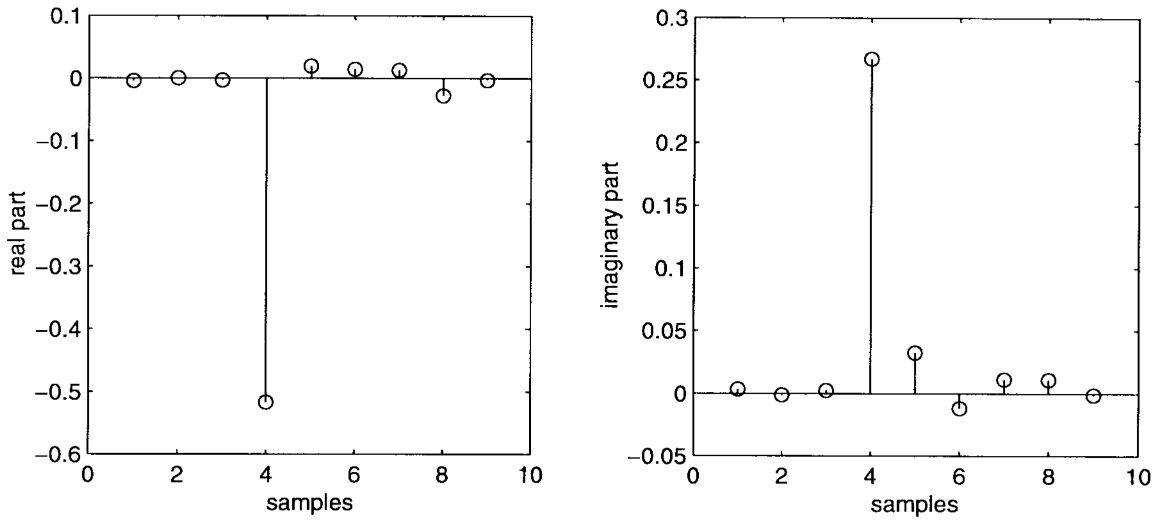


Fig. 2. Real and imaginary parts of the overall system impulse response after CAZE by anchoring to the fourth column.

Because zero-forcing equalizers do not take noise effect into account, we first consider noiseless systems for the development of our zero-forcing equalizers. For noiseless systems

$$\boldsymbol{o}(m) = \boldsymbol{A}\boldsymbol{s}(m) = \boldsymbol{A}\boldsymbol{I}_A\boldsymbol{s}(m) = \boldsymbol{A}\boldsymbol{s}_0(m) \tag{8}$$

where it is defined that

$$\boldsymbol{s}_0(m) \triangleq \boldsymbol{I}_A\boldsymbol{s}(m) = \begin{bmatrix} \boldsymbol{\alpha}_0(m) \\ \boldsymbol{\alpha}_0(m-1) \\ \vdots \\ \boldsymbol{\alpha}_0(m-L-M) \end{bmatrix}. \tag{9}$$

Note that $\boldsymbol{\alpha}_0(m)$ is the same as the source signal $\boldsymbol{\alpha}(m)$ except for some possible zero entries corresponding to zero columns in $\boldsymbol{A}$. In other words, $\boldsymbol{s}_0(m)$ now only contains signal entries that can affect the output signal vector $\boldsymbol{o}(m)$. Thus, they are the only signals that can be recovered from $\boldsymbol{o}(m)$.

We now form the basic matrices for equalization

$$\boldsymbol{P}_k \triangleq \boldsymbol{R}(k)\boldsymbol{R}(0)^{\#} = \boldsymbol{A}\boldsymbol{J}^{kd}\boldsymbol{A}^{\dagger}\left(\boldsymbol{A}\boldsymbol{A}^{\dagger}\right)^{\#}. \tag{10}$$

This matrix can generate an output signal vector

$$\begin{aligned}\boldsymbol{P}_k\boldsymbol{o}(m) &= \boldsymbol{A}\boldsymbol{J}^{kd}\boldsymbol{A}^{\dagger}\left(\boldsymbol{A}\boldsymbol{A}^{\dagger}\right)^{\#}\boldsymbol{A}\boldsymbol{s}(m) \\ &= \boldsymbol{A}\boldsymbol{J}^{kd}\boldsymbol{I}_A\boldsymbol{s}(m) = \boldsymbol{A}\boldsymbol{J}^{kd}\boldsymbol{s}_0(m).\end{aligned} \tag{11}$$

Note that matrix $\boldsymbol{A}\boldsymbol{J}^d$ shifts all the columns of $\boldsymbol{A}$ to the left by d and as a result, $\boldsymbol{A}\boldsymbol{J}^{kd}$ is a matrix whose first $(M'-k)$ block columns are the last $(M'-k)$ block columns of $\boldsymbol{A}$ while the rests have been forced to zero. Choosing $k = M'-1$, $\boldsymbol{A}\boldsymbol{J}^{kd}$ is ISI free, in which only the first block column is nonzero and is the last block column of $\boldsymbol{A}$. Therefore, $\boldsymbol{P}_{M'-1}$ is a zeroforcing equalizer.

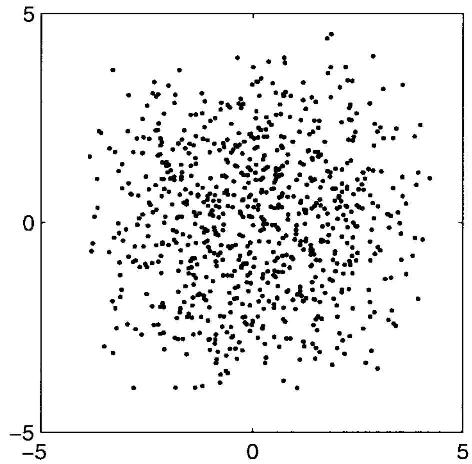
Similarly, we can define another matrix

$$\boldsymbol{Q}_k \triangleq \boldsymbol{R}(-k)\boldsymbol{R}(0)^{\#} = \boldsymbol{A}\boldsymbol{J}^{-kd}\boldsymbol{A}^{\dagger}\left(\boldsymbol{A}\boldsymbol{A}^{\dagger}\right)^{\#} \tag{12}$$

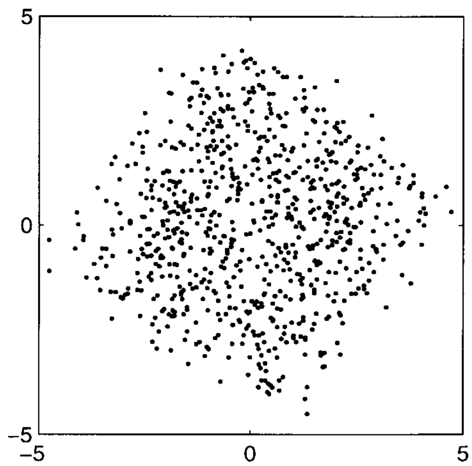
which yields an output signal

$$\boldsymbol{Q}_k\boldsymbol{o}(m) = \boldsymbol{A}\boldsymbol{J}^{-kd}\boldsymbol{I}_A\boldsymbol{s}(m) = \boldsymbol{A}\boldsymbol{J}^{-kd}\boldsymbol{s}_0(m). \tag{13}$$

As $\boldsymbol{J}^{-1}$ shifts columns to the right by one, $\boldsymbol{A}\boldsymbol{J}^{-kd}$ consists of k zero block columns followed by the first $(M'-k)$ block



(a)



(b)

Fig. 3. Eyes diagrams of the received signals under SNR = 25 dB: (a) channel one output and (b) channel two output.

columns of $\boldsymbol{A}$. Once again, for $k = M' - 1$, $\boldsymbol{A}\boldsymbol{J}^{-kd}\boldsymbol{I}_A$ is the ISI free whose last block column is nonzero and is the first block column of $\boldsymbol{A}$.

Both $\boldsymbol{Q}_k$ and $\boldsymbol{P}_k$ reduce the amount of ISI as k increases. When $k = M' - 1$

$$\boldsymbol{P}_{M'-1}\boldsymbol{o}(m) = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \boldsymbol{H}(M)\boldsymbol{\alpha}_0(m) \end{bmatrix}$$

$$\boldsymbol{Q}_{M'-1}\boldsymbol{o}(m) = \begin{bmatrix} \boldsymbol{H}(0)\boldsymbol{\alpha}_0(m - M' + 1) \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

which means that they are in fact both zeroforcing equalizers by column shifting. However, two practical considerations render them useless. First, the actual length of M' depends on the channel length and is in fact unknown to the receiver. It is almost impossible to have an accurate channel order estimate for an exact column shifting. Second, due to the low-pass nature of the channel, the leading and the trailing elements of impulse response $\boldsymbol{H}(0)$ and $\boldsymbol{H}(M)$ tend to be very small. Thus, keeping the first or last column of $\boldsymbol{A}$ tends to generate

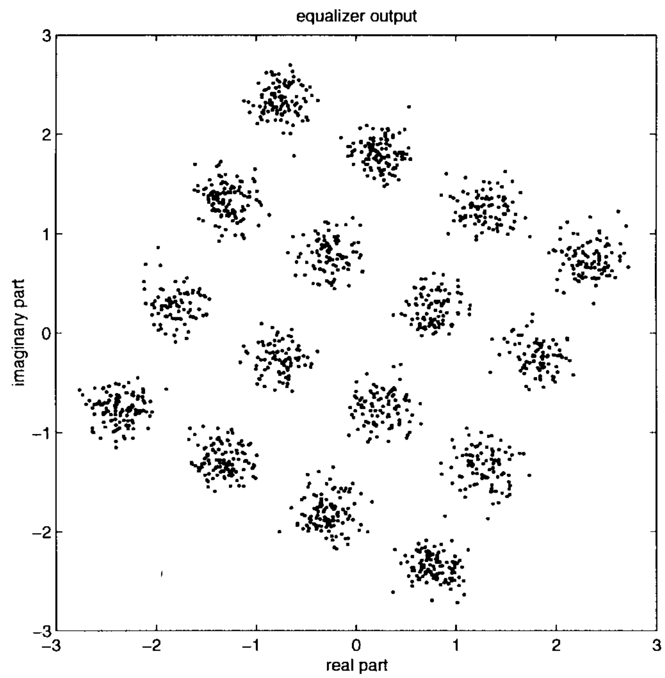


Fig. 4. Eyes diagram of the equalized output after CAZE by anchoring the fourth column under SNR = 25 dB.

output signals with very low signal power and consequently very low signal-to-noise ratio (SNR).

In order to overcome both problems, we now present two methods that can anchor a preselected block column for zeroforcing equalization.

B. Fixed Delay Column Anchoring

Recall the original definition of signal vector $\boldsymbol{s}(m)$ and the shifting property of $\boldsymbol{J}$ matrix. If we denote $\underline{0}_{kd}$ as a $kd \times 1$ zero vector, then

$$\boldsymbol{J}^{(k-1)d}\boldsymbol{s}_0(m) = \begin{bmatrix} \underline{0}_{(k-1)d} \\ \boldsymbol{\alpha}_0(m) \\ \boldsymbol{\alpha}_0(m-1) \\ \vdots \\ \boldsymbol{\alpha}_0(m - M' + k) \end{bmatrix}$$
$$\boldsymbol{J}^{kd}\boldsymbol{s}_0(m-1) = \begin{bmatrix} \underline{0}_{(k-1)d} \\ \underline{0}_d \\ \boldsymbol{\alpha}_0(m-1) \\ \vdots \\ \boldsymbol{\alpha}_0(m - M' + k) \end{bmatrix}. \tag{14}$$

From (11), we can obtain

$$\begin{aligned} \boldsymbol{e}(m) &= \boldsymbol{P}_{k-1}\boldsymbol{o}(m) - \boldsymbol{P}_k\boldsymbol{o}(m-1) \\ &= \boldsymbol{A}\boldsymbol{J}^{(k-1)d}\boldsymbol{s}_0(m) - \boldsymbol{A}\boldsymbol{J}^{kd}\boldsymbol{s}_0(m-1) \qquad (15) \\ &= \boldsymbol{A}\left[\boldsymbol{J}^{(k-1)d}\boldsymbol{s}_0(m) - \boldsymbol{J}^{kd}\boldsymbol{s}_0(m-1)\right] \\ &= \boldsymbol{A}\begin{bmatrix} \underline{0}_{(k-1)d} \\ \boldsymbol{\alpha}_0(m) \\ \underline{0}_{(M'-k)d} \end{bmatrix} \\ &= \boldsymbol{h}(k)\boldsymbol{\alpha}_0(m) \qquad (16) \end{aligned}$$

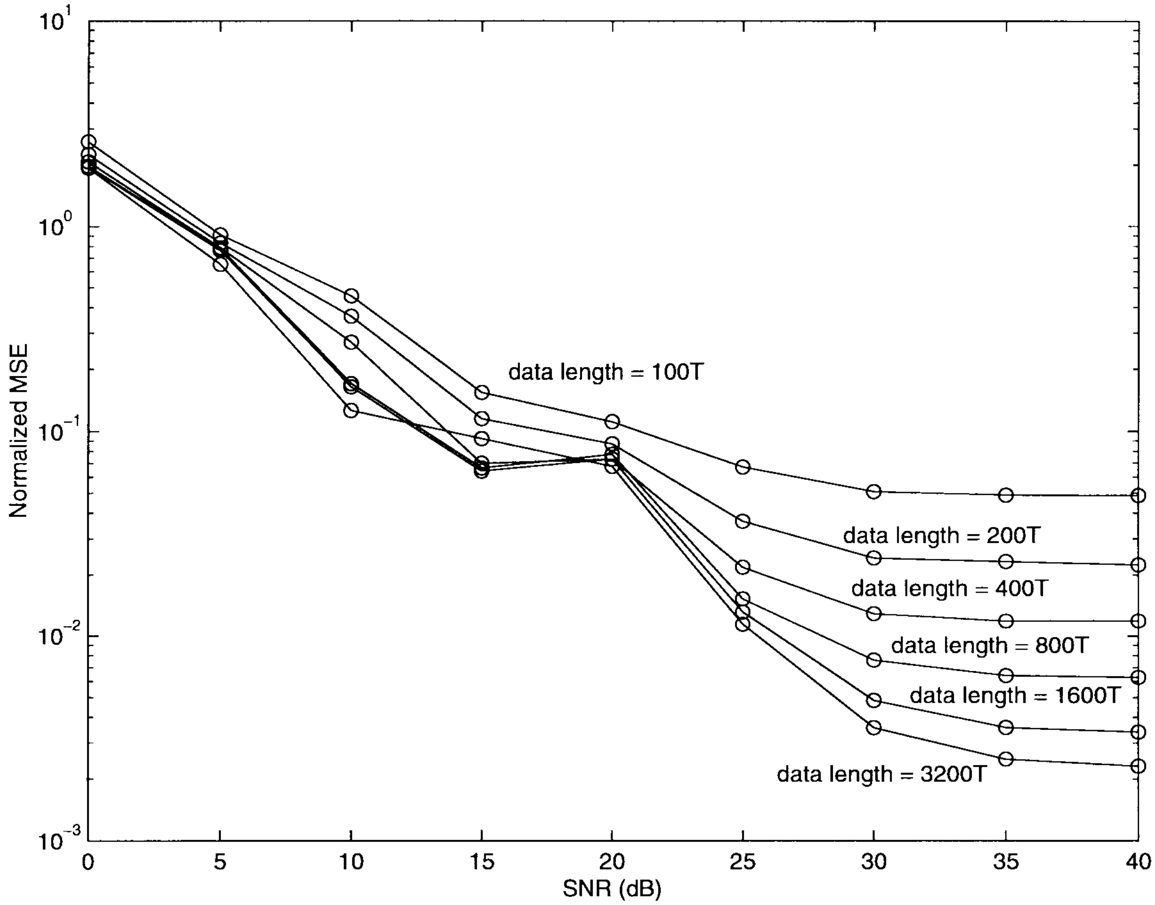


Fig. 5. Normalized MSE of CAZE output for different data received lengths and SNR levels.

where we have defined the kth block column of $\boldsymbol{A}$ as $\boldsymbol{h}(k)$

$$\boldsymbol{h}(k) \triangleq \begin{bmatrix} \boldsymbol{H}(k-1) \\ \boldsymbol{H}(k-2) \\ \vdots \\ \boldsymbol{H}(k-L-1) \end{bmatrix}$$

in which $\boldsymbol{H}(n) = 0$ for $n < 0$ or $n > M$.

Hence, we have successfully anchored the kth block column of $\boldsymbol{A}$ by eliminating all other columns. In fact, we can anchor any block column $\boldsymbol{h}(k)$ by selecting k such that the resulting signal $\boldsymbol{e}(m)$ is ISI free. Because the equalizer output signal has a fixed delay of zero, we name this algorithm forward fixed-delay CAZE (forward FD-CAZE).

Similarly, reverse shift can be realized through

$$\begin{aligned} \boldsymbol{e}(m) &= \boldsymbol{Q}_{k-1}\boldsymbol{o}(m-1) - \boldsymbol{Q}_k\boldsymbol{o}(m) \\ &= \boldsymbol{h}(M'-k+1)\boldsymbol{\alpha}_0(m-M') \end{aligned} \tag{17}$$

which we shall call reverse FD-CAZE.

In the reverse FD-CAZE, it should be noted that certain elements in $\boldsymbol{\alpha}_0(m-M')$ may be zero. Hence, regardless of the choice of k, user signals absent from $\boldsymbol{H}(M)$ will be missing from the recovered signal $\boldsymbol{e}(m)$. This implies that the ensuing task of source separation is made easier. On the other hand, this is also a drawback. Zero elements in $\boldsymbol{\alpha}_0(m-M')$ also imply that reverse FD-CAZE cannot extract all source signals if there are all zero columns in $\boldsymbol{H}(M)$. Next, we develop a different column-anchoring approach that does not share this weakness.

C. Delay Selectable Column Anchoring

In Section III-B, column anchoring is achieved by aligning signals generated by $\boldsymbol{P}_{k-1}$ and $\boldsymbol{P}_k$ (or $\boldsymbol{Q}_{k-1}$ and $\boldsymbol{Q}_k$). The recovered signals from forward (or reverse) FD-CAZE must come from signal arrivals with zero (or maximum) delay.

Here we shall present a different column anchoring strategy without shifting output signals. Observe that

$$\boldsymbol{J}^{kd}\boldsymbol{J}^{-kd} = \begin{bmatrix} \boldsymbol{0}_{kd\times kd} & \boldsymbol{0}_{kd\times(M'-k)d} \\ \boldsymbol{0}_{(M'-k)d\times kd} & \boldsymbol{I}_{(M'-k)d} \end{bmatrix}$$

$$\boldsymbol{J}^{-kd}\boldsymbol{J}^{kd} = \begin{bmatrix} \boldsymbol{I}_{(M'-k)d} & \boldsymbol{0}_{(M'-k)d\times kd} \\ \boldsymbol{0}_{kd\times(M'-k)d} & \boldsymbol{0}_{kd\times kd} \end{bmatrix}$$

where $\boldsymbol{0}_{n\times m}$ is an $n \times m$ zero matrix and $\boldsymbol{I}_{(M'-k)d}$ is the identity matrix with dimension $(M'-k)d$. From the observations regarding $\boldsymbol{I}_A$, we have

$$\boldsymbol{I}_A\boldsymbol{J}^{kd}\left(\boldsymbol{I}_A - \boldsymbol{J}^d\boldsymbol{I}_A\boldsymbol{J}^{-d}\right)\boldsymbol{J}^{-kd} = \boldsymbol{I}_A\boldsymbol{J}^{kd}\left(\boldsymbol{I} - \boldsymbol{J}\boldsymbol{J}^{-d}\right)\boldsymbol{J}^{-kd}. \tag{18}$$

We can now proceed. Based on the definition of $\boldsymbol{I}_A$ and (7), we have

$$\begin{aligned} \boldsymbol{P}_k\boldsymbol{Q}_k &= \boldsymbol{A}\boldsymbol{J}^{kd}\boldsymbol{I}_A\boldsymbol{J}^{-kd}\boldsymbol{A}^{\dagger}\left(\boldsymbol{A}\boldsymbol{A}^{\dagger}\right)^{\#} \\ &= \boldsymbol{A}\boldsymbol{I}_A\boldsymbol{J}^{kd}\boldsymbol{I}_A\boldsymbol{J}^{-kd}\boldsymbol{A}^{\dagger}\left(\boldsymbol{A}\boldsymbol{A}^{\dagger}\right)^{\#}. \end{aligned} \tag{19}$$

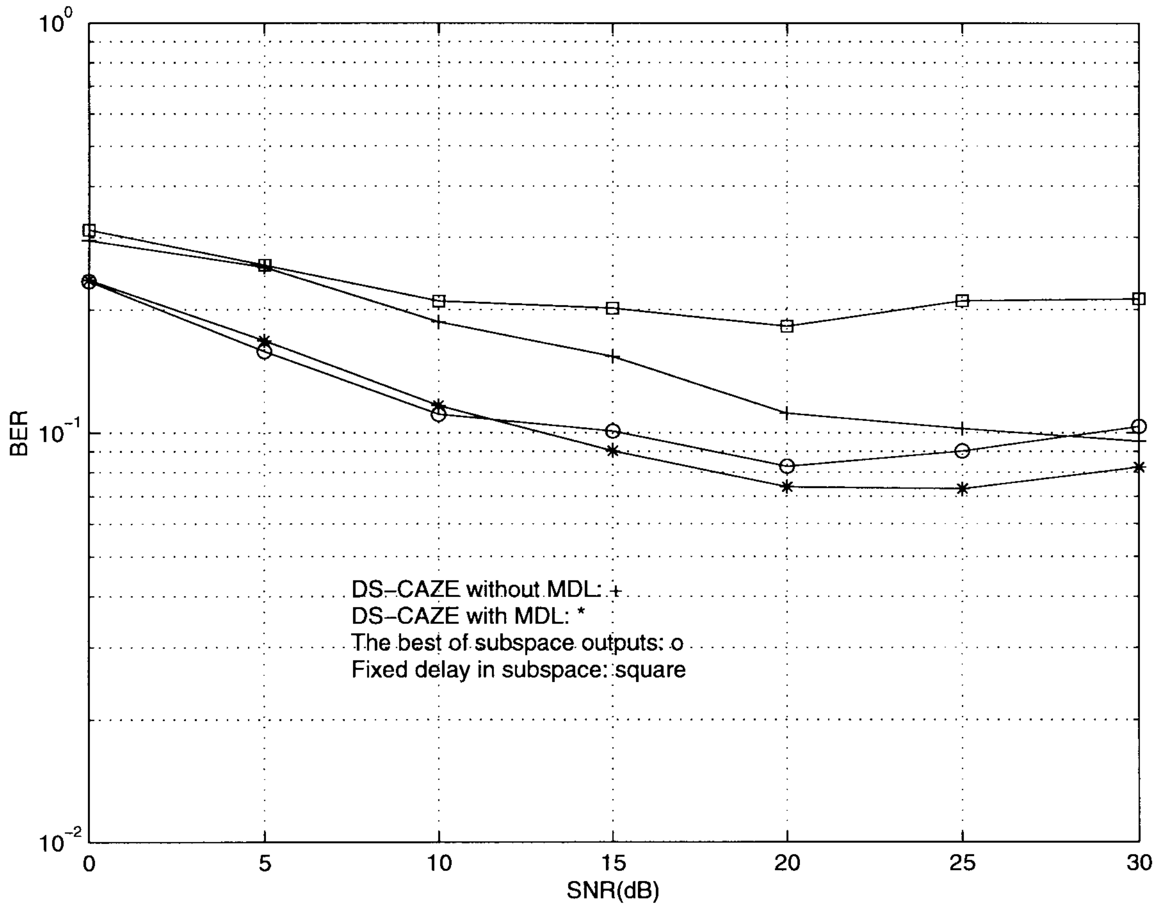


Fig. 6. BER of DS-CAZE and SSM based on MDL rank estimate for "Bad Urban" channels.

Thus, from (18), we have

$$\begin{aligned}&\boldsymbol{P}_k\boldsymbol{Q}_k - \boldsymbol{P}_{k+1}\boldsymbol{Q}_{k+1}\\ &= \boldsymbol{A}\boldsymbol{I}_A\left(\boldsymbol{J}^{kd}\boldsymbol{I}_A\boldsymbol{J}^{-kd} - \boldsymbol{J}^{(k+1)d}\boldsymbol{I}_A\boldsymbol{J}^{-(k+1)d}\right)\boldsymbol{A}^{\dagger}(\boldsymbol{A}\boldsymbol{A}^{\dagger})^{\#}\\ &= \boldsymbol{A}\boldsymbol{I}_A\boldsymbol{J}^{kd}\left(\boldsymbol{I}_A - \boldsymbol{J}^{d}\boldsymbol{I}_A\boldsymbol{J}^{-d}\right)\boldsymbol{J}^{-kd}\boldsymbol{A}^{\dagger}\left(\boldsymbol{A}\boldsymbol{A}^{\dagger}\right)^{\#}\\ &= \boldsymbol{A}\boldsymbol{I}_A\boldsymbol{J}^{kd}\left(I - \boldsymbol{J}^{d}\boldsymbol{J}^{-d}\right)\boldsymbol{J}^{-kd}\boldsymbol{A}^{\dagger}\left(\boldsymbol{A}\boldsymbol{A}^{\dagger}\right)^{\#}\\ &= \boldsymbol{A}\boldsymbol{J}^{kd}\left(I - \boldsymbol{J}^{d}\boldsymbol{J}^{-d}\right)\boldsymbol{J}^{-kd}\boldsymbol{A}^{\dagger}\left(\boldsymbol{A}\boldsymbol{A}^{\dagger}\right)^{\#}.\end{aligned} \tag{20}$$

The critical matrix

$$\boldsymbol{J}^{kd}(I - \boldsymbol{J}^{d}\boldsymbol{J}^{-d})\boldsymbol{J}^{-kd} = \begin{bmatrix} \boldsymbol{0}_{kd\times kd} & \boldsymbol{0}_{kd\times d} & \boldsymbol{0}_{kd\times(M'-k-1)d}\\ \boldsymbol{0}_{d\times kd} & \boldsymbol{I}_d & \boldsymbol{0}_{d\times(M'-k-1)d}\\ \boldsymbol{0}_{(M'-k-1)d\times kd} & \boldsymbol{0}_{(M'-k-1)d\times d} & \boldsymbol{0}_{(M'-k-1)d\times(M'-k-1)} \end{bmatrix} \tag{21}$$

is zero except for its $(k+1,\, k+1)$th block entry $\boldsymbol{I}_d$. Hence, define

$$\begin{aligned}\boldsymbol{D}_k &\triangleq \boldsymbol{A}\left(\boldsymbol{J}^{kd}\boldsymbol{J}^{-kd} - \boldsymbol{J}^{(k+1)d}\boldsymbol{J}^{-(k+1)d}\right)\\ &= \left[\boldsymbol{0}_{N(L+1)\times kd} \quad \boldsymbol{h}(k+1) \quad \boldsymbol{0}_{N(L+1)\times(M'-k-1)d}\right].\end{aligned}$$

An ISI-free equalizer output can then be obtained as

$$\begin{aligned}\boldsymbol{e}(m) &= (\boldsymbol{P}_k\boldsymbol{Q}_k - \boldsymbol{P}_{k+1}\boldsymbol{Q}_{k+1})\boldsymbol{o}(m) = \boldsymbol{D}_k\boldsymbol{I}_A\boldsymbol{s}(m)\\ &= \boldsymbol{D}_k\boldsymbol{s}_0(m) = \boldsymbol{h}(k+1)\boldsymbol{\alpha}_0(m-k)\\ &= \boldsymbol{h}(k+1)\boldsymbol{\alpha}(m-k)\end{aligned} \tag{22}$$

where the last equality holds because of the corresponding positions of all-zero columns in $\boldsymbol{h}(k+1)$ and all-zero elements in $\boldsymbol{\alpha}_0(m-k)$. Because its output delay can be selected according to the anchor k, this equalizer is named forward delay selectable CAZE (forward DS-CAZE).

Similarly, by exchanging the roles of $\boldsymbol{P}_k$ and $\boldsymbol{Q}_k$, we have

$$\begin{aligned}\boldsymbol{e}(m) &= \left(\boldsymbol{Q}_{k-1}\boldsymbol{P}_{k-1} - \boldsymbol{Q}_k\boldsymbol{P}_k\right)\boldsymbol{o}(m)\\ &= \boldsymbol{h}(M'-k+1)\boldsymbol{\alpha}(m-M'+k).\end{aligned} \tag{23}$$

This equalizer will be referred to as the reverse DS-CAZE.

Remarks:

- Both forward and reverse DS-CAZE algorithms can extract source signals with zero ISI so long as the anchored columns are not all zero. Unlike in reverse FD-CAZE, the last d columns of matrix $\boldsymbol{A}$ do not have to be nonzero. This is one of the major differences between the two CAZE approaches.
- If the selected columns do not contain a given source signal, a different block of columns should be chosen again in order to extract the missing source signal.

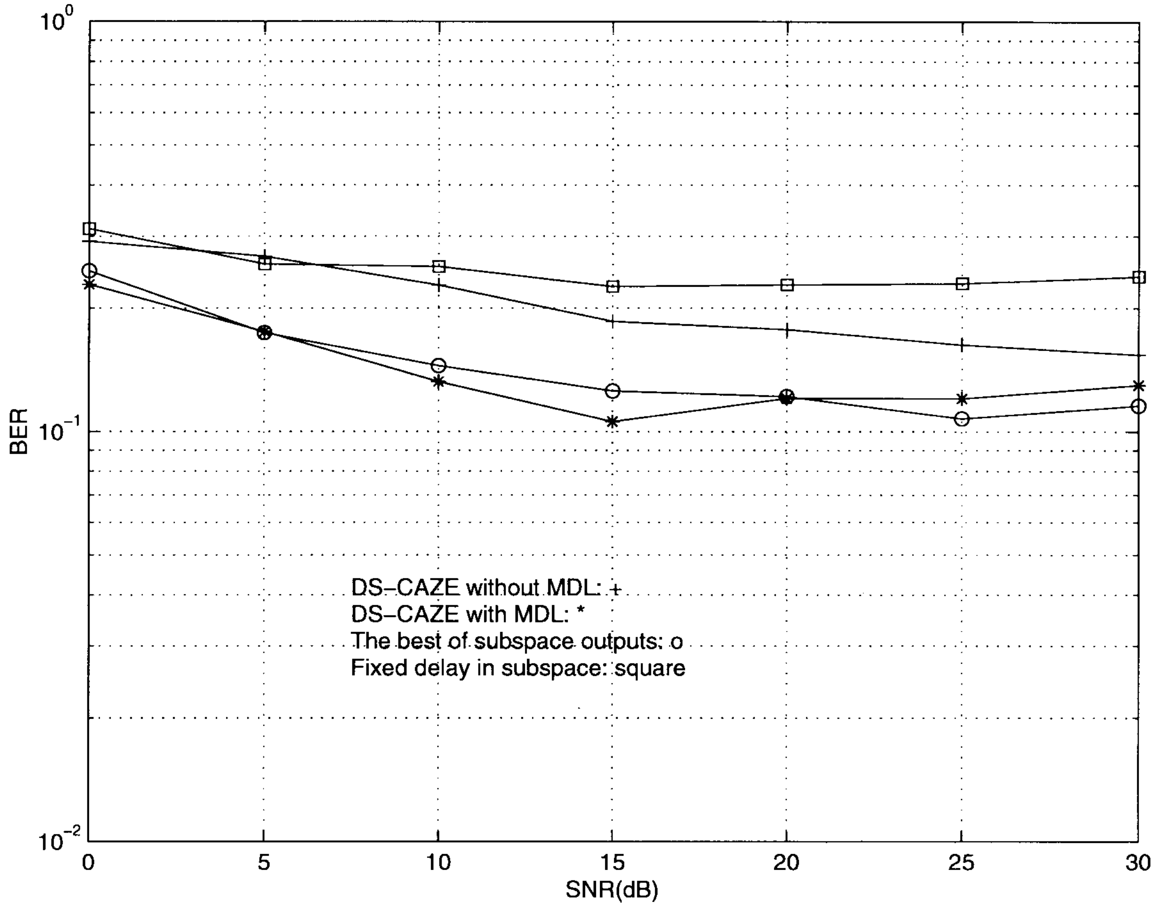


Fig. 7. BER of DS-CAZE and SSM based on MDL rank estimate for "Hilly Terrain" channels.

- In order to recover the symbol sequence of a single user, blind source separation algorithms [15]–[17] may be applied on $\boldsymbol{e}(m)$ for CCI cancellation after ISI zeroforcing.
- In fact, based on (19) and (20), we have for any positive integer n

$$\begin{aligned}(\boldsymbol{P}_k\boldsymbol{Q}_k)^n &= \boldsymbol{A}\left(\boldsymbol{I}_A\boldsymbol{J}^{kd}\boldsymbol{I}_A\boldsymbol{J}^{-kd}\boldsymbol{I}_A\right)^n\boldsymbol{A}^\dagger\left(\boldsymbol{A}\boldsymbol{A}^\dagger\right)^\# \\ &= \boldsymbol{A}\boldsymbol{J}^{kd}\boldsymbol{I}_A\boldsymbol{J}^{-kd}\boldsymbol{A}^\dagger\left(\boldsymbol{A}\boldsymbol{A}^\dagger\right)^\# \\ &= \boldsymbol{P}_k\boldsymbol{Q}_k\end{aligned}$$

and

$$\left(\boldsymbol{P}_k\boldsymbol{Q}_k - \boldsymbol{P}_{k+1}\boldsymbol{Q}_{k+1}\right)^n = \boldsymbol{P}_k\boldsymbol{Q}_k - \boldsymbol{P}_{k+1}\boldsymbol{Q}_{k+1}. \tag{24}$$

Therefore, column anchored zeroforcing equalization can be accomplished also by

$$\begin{aligned}\boldsymbol{e}(m) &= \left[(\boldsymbol{P}_k\boldsymbol{Q}_k)^{n_1} - (\boldsymbol{P}_{k+1}\boldsymbol{Q}_{k+1})^{n_2}\right]^{n_3}\boldsymbol{o}(m) \\ &= \boldsymbol{h}(k)\boldsymbol{\alpha}(m-k+1)\end{aligned} \tag{25}$$

with any positive integer n_1, n_2, n_3. Similarly, generalization can be made to the reverse DS-CAZE

$$\begin{aligned}\boldsymbol{e}(m) &= \left[(\boldsymbol{Q}_{k-1}\boldsymbol{P}_{k-1})^{n_1} - (\boldsymbol{Q}_k\boldsymbol{P}_k)^{n_2}\right]^{n_3}\boldsymbol{o}(m) \\ &= \boldsymbol{h}(M'-k+1)\boldsymbol{\alpha}(m-M'+k).\end{aligned} \tag{26}$$

It should be noted, however, that such a generalization is only mathematically attractive. It may not be practically helpful because of its increased computational cost and possible enhancement of estimation errors due to the large number of matrix multiplications involved.

- It should be noted that in [19], a different zeroforcing blind equalizer was proposed. Our method here uses a matrix operator that generates a vector of channel input estimates by cancelling ISI dynamics while the algorithm of [19] searches for a single equalizer filter.

D. Channel Noise Considerations

It should be noted that both FD-CAZE and DS-CAZE are derived from the noise-free channel assumption. When additive white channel noise with variance σ^2 is presented, the auto-covariance matrices become

$$\boldsymbol{R}(k) = \boldsymbol{A}\boldsymbol{J}^{kd}\boldsymbol{A}^\dagger + \sigma^2\boldsymbol{J}^{kN}, \qquad k = 0, \pm 1, \pm 2, \ldots . \tag{27}$$

The noise contribution may be subtracted if the noise level σ^2 is known.

When the noise level is unknown, σ^2 can be estimated from the singular value decomposition (SVD) of $\boldsymbol{R}(0)$. Since SVD of $\boldsymbol{R}(0)$ is useful for calculating its pseudoinverse, no additional computation cost is incurred in the SVD step. However, it should be cautioned that removal of noise contribution by subtraction often results in poorer performance and is not recommended.

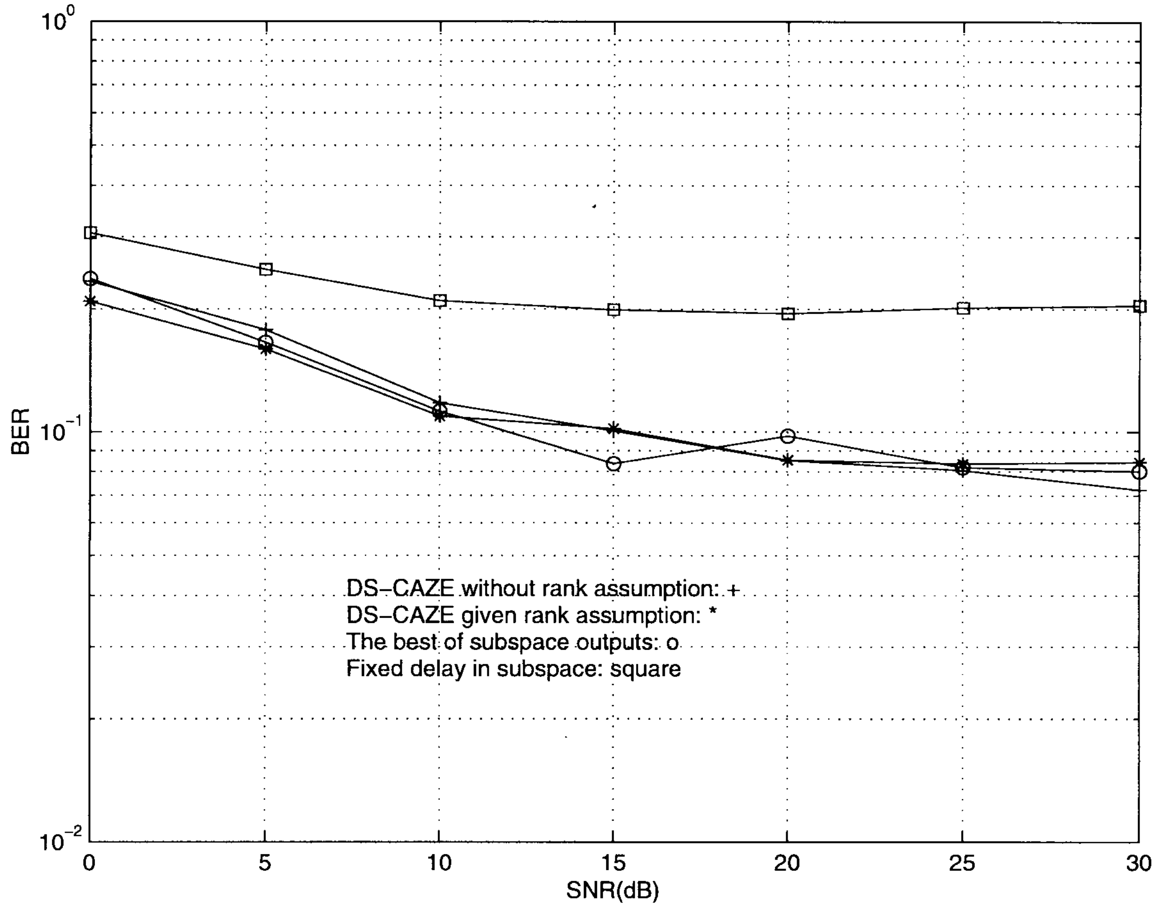


Fig. 8. BER of DS-CAZE and SSM based on fixed channel length assumption $M = 3$ for "Bad Urban" channels.

In our implementation, the noise contribution will not be subtracted from $\boldsymbol{R}(k)$. In fact, we only estimate the rank and consequently the pseudoinverse of $\boldsymbol{R}(0)$ for noisy channels. Unlike in channel identification, the estimated rank does not affect the length of the equalizer filters. Hence the error in rank estimation only affects the system performance via $\boldsymbol{R}(0)^{\#}$ and has less impact.

For FD-CAZE, additive channel noise has an additional effect on equalizer performance. Because of the signal subtraction in (15), noise tends to be enhanced. For DS-CAZE, there is no signal subtraction. However, DS-CAZE relies on $\boldsymbol{P}_k\boldsymbol{Q}_k$ matrix product which can enhance numerical errors. Thus, the actual channel condition and system setup will determine which algorithm performs better.

IV. CAZE in Single-User Systems

In Section III, we have derived several CAZE algorithms that can cancel ISI by anchoring a block column of the channel convolution matrix $\boldsymbol{A}$. With these methods, blind equalizers for a single-user system ($d = 1$) can be designed easily. However, even in a single-user communication system, the estimate $\boldsymbol{e}(m)$ still generates multiple outputs. There are $N(L+1)$ components in $\boldsymbol{e}(m)$, each of which can be viewed as an estimate of the desired symbol sequence. When the received signals are corrupted by additive noises $\boldsymbol{w}(m)$, SNR in each component of $\boldsymbol{e}(m)$ is different. In what follows, we will propose several strategies for determining the final single-user output.

A. The Maximum Likelihood Estimate

Let $\boldsymbol{n}(m)$ be the noise in $\boldsymbol{o}(m)$. Then (2) becomes

$$\boldsymbol{o}(m) = \boldsymbol{A}\boldsymbol{s}(m) + \boldsymbol{n}(m). \tag{28}$$

We first derive the maximum likelihood estimate of the user input for DS-CAZE algorithms. For a preselected column k, an output vector is obtained as

$$\boldsymbol{e}(m) = \boldsymbol{G}\boldsymbol{o}(m) = \boldsymbol{h}(k+1)\boldsymbol{\alpha}(m-k) + \boldsymbol{G}\boldsymbol{n}(m) \tag{29}$$

where

$$\boldsymbol{G} = \boldsymbol{P}_k\boldsymbol{Q}_k - \boldsymbol{P}_{k+1}\boldsymbol{Q}_{k+1}$$

is assumed to be ideal and removes all ISI in $\boldsymbol{e}(m)$. If the noise $\boldsymbol{n}(m)$ is white Gaussian, the maximum likelihood estimate of the input symbol sequence is

$$\boldsymbol{\alpha}(m-k) = \frac{1}{||\boldsymbol{h}(k+1)||^2}\,\boldsymbol{h}(k+1)^{\dagger}(\boldsymbol{G}\boldsymbol{G}^{\dagger})^{\#}\boldsymbol{e}(m). \tag{30}$$

To estimate $\boldsymbol{h}(k)$, consider the covariance matrix of $\boldsymbol{e}(m)$

$$\boldsymbol{R}_e = E\{\boldsymbol{e}(m)\boldsymbol{e}(m)^{\dagger}\} = \boldsymbol{h}(k+1)\boldsymbol{h}(k+1)^{\dagger} + \sigma_w^2\boldsymbol{G}\boldsymbol{G}^{\dagger} \tag{31}$$

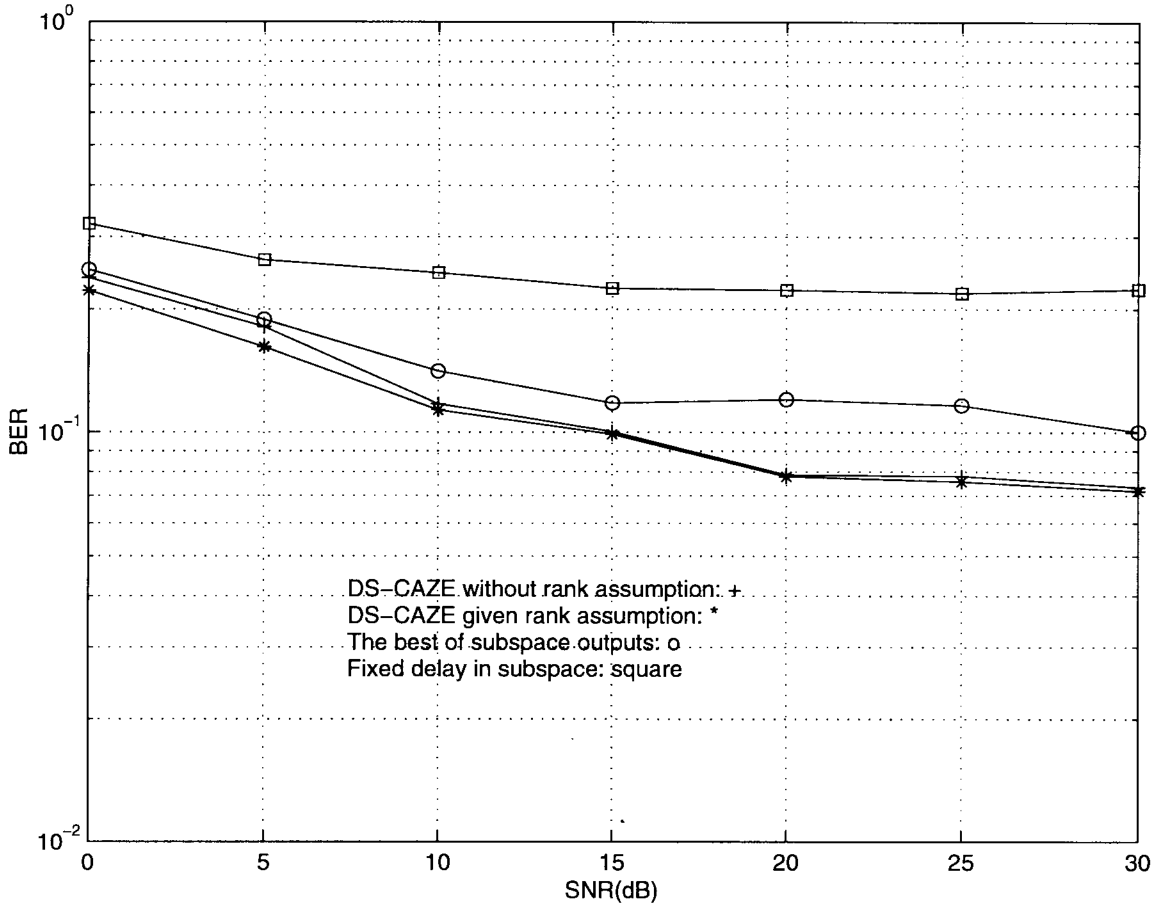


Fig. 9. BER of DS-CAZE and SSM based on fixed channel length assumption $M = 4$ for "Bad Urban" channels.

where all noise components are assumed to have the same variance σ_w^2. Observe from (20) that

$$\boldsymbol{G}\boldsymbol{G}^\dagger = \hat{a}_{kk}\boldsymbol{h}(k+1)\boldsymbol{h}(k+1)^\dagger \tag{32}$$

where $\hat{a}_{kk}$ is the (k, k)th entries of $\boldsymbol{A}^{\#}(\boldsymbol{A}^{\#})^\dagger$. Thus, if $\hat{a}_{kk}$ is nonzero, we can find $\boldsymbol{h}(k+1)$ as the eigenvector of $\boldsymbol{G}\boldsymbol{G}^\dagger$ corresponding to the largest eigenvalue. Otherwise, we need to form

$$\boldsymbol{R}_e = \left(1 + \sigma_w^2 \hat{a}_{kk}\right)\boldsymbol{h}(k+1)\boldsymbol{h}(k+1)^\dagger \tag{33}$$

which implies that $\boldsymbol{R}_e$ is a rank one matrix and is spanned by $\boldsymbol{h}(k)$. The vector $\boldsymbol{h}(k)$ is then the dominant vector in the space of $\boldsymbol{R}_e$. Hence, $\boldsymbol{h}(k)$ can be determined as the eigenvector of $\boldsymbol{R}_e$ associated with the largest eigenvalue. Noting that $\boldsymbol{G}\boldsymbol{G}^\dagger$ is rank one, the maximum likelihood estimate can be simplified as

$$\boldsymbol{\alpha}(m-k) = \boldsymbol{h}(k+1)^\dagger \boldsymbol{e}(m). \tag{34}$$

For the maximum likelihood estimate of input sequence in FD-CAZE algorithms, the estimate becomes more complicated as the filtered noise covariance no longer has rank one. However, assuming that channel noise is very weak, the estimate by (34) can be used in the same way.

B. Single-Output Selections

A simpler approach to determine the single channel input may be to select one of the best equalizer outputs $e_i(m)$. This may be particularly true for FD-CAZE algorithms.

One selection is to choose the one component of $\boldsymbol{e}(m)$ with the maximum SNR in DS-CAZE. Let $g_{i,k}$ be the (i, k)th component of matrix $\boldsymbol{G}$ and h_i the ith component of $\boldsymbol{h}(k)$. By assuming that the ISI in $\boldsymbol{e}(m)$ has been removed, we have

$$\frac{E\{|e_i(m)|^2\}}{|g_{i,k}|^2} = \sigma_w^2(\mathrm{SNR}_i + 1) \tag{35}$$

where SNR_i is the SNR of the ith component of $\boldsymbol{e}(m)$ defined by

$$\mathrm{SNR}_i = \frac{|h_i|^2}{\sigma_w^2 |g_{i,k}|^2}.$$

To select an output $e_i(m)$ with the maximum SNR, we can choose the output so that the left-hand side of (35) is maximized.

In fact, the simplest selection is to find the equalized output with the maximum energy as we will do in simulations that follow.

C. Column Selection

In general, middle columns of $\boldsymbol{A}$ with large norms should be selected as they provide the strongest signal contents. Without

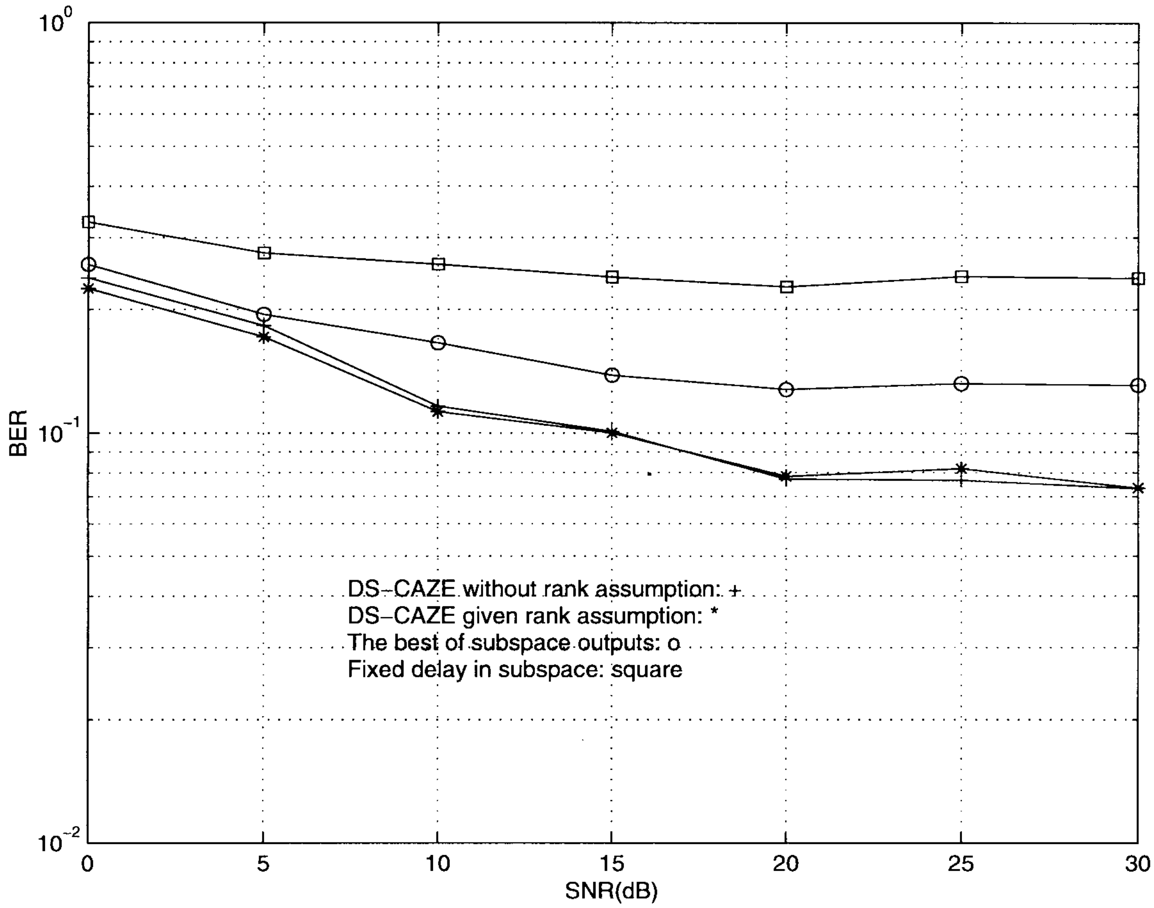


Fig. 10. BER of DS-CAZE and SSM based on fixed channel length assumption $M = 5$ for "Bad Urban" channels.

prior knowledge on the size of $\boldsymbol{A}$, we can generally select the Mth (block) column where M is the estimated channel length. Alternatively, we can also generate several outputs from multiple column anchors and select the anchor with the strongest output signal.

Both FD-CAZE and DS-CAZE can be directly applied for multiple column anchors. By choosing different delay constant k, the algorithm does not need to recompute $\boldsymbol{R}(0)^{\#}$ for each delay (column). Hence, with only a modest increase in computation cost, multiple column anchors can generate multiple output signals with different delays.

V. Simulation Examples

A. Linear Multipath Channels

In this experiment, the forward DS-CAZE algorithm with maximum likelihood output estimate is applied to a multipath channel. We select a transmitter with raised-cosine pulse $p(t)$ whose roll-off factor is $\beta = 0.1$. The raised-cosine pulse $p(t)$ is truncated to $4T$, where T is the baud period. The channel is a two-ray multipath which results in an overall channel impulse response of

$$h(t) = p(t) - 0.5(1 + j)p(t - T/3). \tag{36}$$

A single-user input of uniform 16 QAM is transmitted. The received signal is oversampled by a factor of two. The channel impulse response is shown in Fig. 1 and it closes the eye for 16 QAM. This simple channel is used to illustrate how zeroforcing can be realized by DS-CAZE in actual QAM systems.

In our simulation, we select $L = 5$ and $k = 4$. Notice that the channel order is unknown and estimated based on the information theoretic criterion minimum description length (MDL) [20]. Thus, the fourth column of the channel convolution matrix will be anchored in DS-CAZE zeroforcing. Under SNR = 25 dB, 800 × 2 received samples are processed. The resulting system impulse response after equalization is shown in Fig. 2. As expected, almost all ISI is eliminated and the fourth coefficient of the overall system impulse response is preserved. Figs. 3 and 4 demonstrate the eye diagrams before and after equalization for SNR = 25 dB. The eyes are clearly opened after equalization.

We now change the channel SNR and the number of available data samples to test their effects on our algorithm. We vary the channel output SNR from 0 to 40 dB and the data length from 100 to $3200T$. The normalized mean square error (NMSE) from residual ISI and noise is used as performance measure. NMSE is defined as MSE normalized by the true signal power. The results of NMSE are obtained by averaging over 100 Monte Carlo simulations and are shown in Fig. 5. The results show that our forward DS-CAZE algorithm is very effective for SNR over 15 dB. In fact, even when the

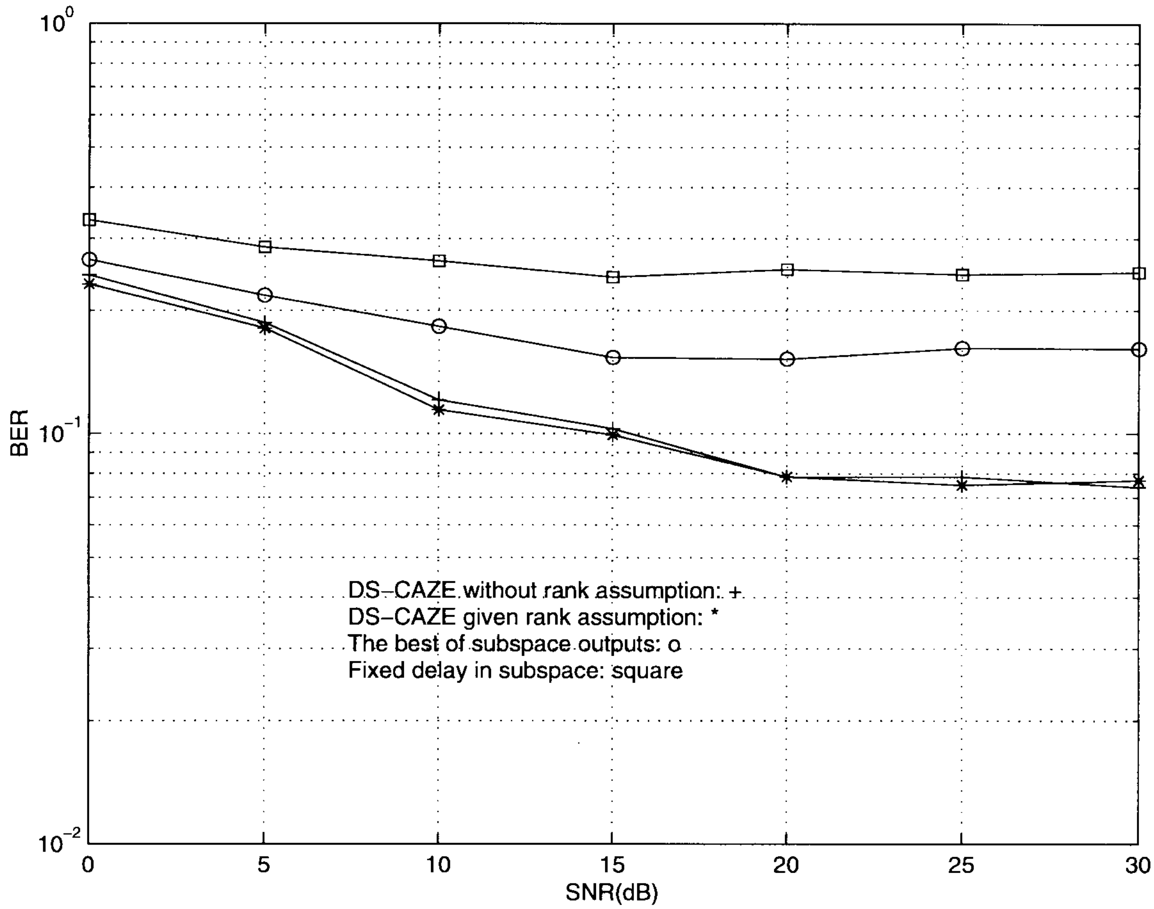


Fig. 11. BER of DS-CAZE and SSM based on fixed channel length assumption $M = 6$ for "Bad Urban" channels.

data length is as short as $100T$, the NMSE is still significantly reduced.

B. Simulation in GSM Systems

Though linear blind equalization may be more suitable for data systems such as telephone network and cable transmissions, its possible application in wireless mobile system has always remained attractive to many researchers. Here we present a simulation example for a wireless system.

GSM is one of the most widely used wireless communications systems. In GSM systems, the modulation scheme is GMSK, which is a nonlinear phase modulation. By a suitable approximation [21], the GSM received signal can be approximated by a linear QAM system. However, because of the short GSM data frame and the linear approximation error, blind equalization in GSM system becomes difficult. In this section, we test the feasibility of the CAZE algorithms in GSM systems.

Because GMSK signal can be modeled as a quasi-QPSK signal with almost no excess bandwidth, SOS algorithms such as CAZE require additional antennas be available. This adds to the hardware RF cost and is undesirable. We will adopt a derotation method as described in [23]. However, we take the real and the imaginary parts of the derotated signal to generate two subchannel outputs. CAZE algorithms can then be applied on these two subchannel outputs. The details of derotation for channel diversity are provided in [24].

We assume that the channel fading over one user data frame is unchanged. The receiver anti-aliasing filter was selected as a root-raised cosine pulse with roll-off factor 0.1. The impulse response is oversampled by a factor of 16. Bit timing extraction is based on maximum sampling power at the receiver filter output. The sampled data are then derotated, separated into two subchannels, and then sent through DS-CAZE. The bit error rate (BER) is employed as the performance measurement.

As we have already mentioned, the channel order is a crucial parameter in almost all SOS-based equalizers. We compare simulation results of DS-CAZE with the well-known subspace method (SSM) presented in [9]. To provide fair comparison, we used the following test conditions.

- Both algorithms use the data length of 10 in $\boldsymbol{o}(m)$ ($L = 9$).
- MDL rank estimation is used for subspace estimation in SSM and for pseudoinverse computation in "DS-CAZE with MDL."
- In "DS-CAZE without MDL," the MDL rank information is not used in computing the pseudoinverse of $\boldsymbol{R}(0)$.
- Channel order estimate based on MDL rank estimation is used directly in SSM for channel estimation and is used as the anchored column for DS-CAZE.
- SSM channel estimate is used to form pseudoinverse of the matrix $\boldsymbol{A}$ for SSM linear equalization.

- DS-CAZE output is compared with the SSM output with the lowest BER and also with the SSM output at the same delay.
- Only maximum energy is used to select the single DS-CAZE output.

In each of the 100 Monte Carlo simulations, the channel was randomly selected as a COST207 [25] hilly terrain or bad urban channel with an additive white Gaussian noise.

The comparative BER's are given in Fig. 6 (Bad Urban) and Fig. 7 (Hilly Terrain). Clearly, the BER of DS-CAZE with MDL is less than even the lowest BER among all SSM outputs. Note that when SSM is implemented, the receiver is at no liberty to select the best linear equalizer output. Thus, in comparing DS-CAZE with SSM linear equalization of the same delay, DS-CAZE significantly outperforms the SSM linear equalizer for both types of channels. It can also be seen that the BER for "hilly terrain" channels is generally higher than for "bad urban" channels. This directly reflects the effect of longer (hilly terrain) channel delay spread on linear equalizers.

We now test the sensitivity of both algorithms to errors in the channel order estimate. Note that we do not know the actual channel length. Let the assumed channel order be $M = 3,\ 4,\ 5,\ 6$, respectively. We choose L according the channel order estimate so that $\boldsymbol{A}$ has minimum size as a rectangular convolution matrix. The equalizer output estimate with the highest energy is used as the equalizer's output.

For "Bad Urban" channels, the resulting BER's of DS-CAZE with and without MDL compared with the BER of SSM outputs are shown in Figs. 8–11. From the comparison of BER's, it can be seen that the performance of DS-CAZE is consistently lower while the BER of the best SSM delay varies significantly. This experiment demonstrates the lower sensitivity of DS-CAZE to channel order estimates.

The main reason for the lower sensitivity of our method is that it is a direct blind equalization approach that does not take the intermediate step of channel estimation. The fact that many existing methods first estimate the channel response and then design the equalizer makes them more sensitive to channel order estimate. It should be stated, however, that the general performance of linear equalizers in GSM systems is much worse than standard nonlinear equalizers such as the Viterbi algorithm. Linear blind equalizers cannot replace nonlinear equalizers in practice. They should only be used when the computation power of the receiver is severely limited and the use of the computationally costly Viterbi algorithms becomes unrealistic.

VI. Conclusion

We developed a simple and effective column-anchored zeroforcing blind equalization strategy for MIMO systems. The CAZE algorithms rely on the SOS of the channel output signals. They do not rely on channel order estimate, as many other SOS algorithms do, and they are less sensitive to errors in the channel matrix rank estimate. The receiver may preselect any block of d columns in the channel convolution matrix. The algorithm development is very simple and easy to implement. Maximum likelihood equalizer output for single user system is derived. Simulation results on QAM systems demonstrate good performance by the CAZE algorithms. The channel assumption allows difference in delay spread for multiple users in asynchronous wireless environment. The linear method of CAZE can be useful in wireless systems where the computational cost severely limits the use of nonlinear methods such as the Viterbi algorithm.

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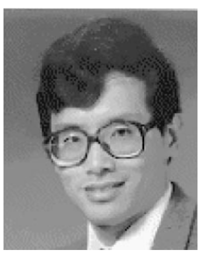

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