Detection of Spatial Modulation Signals in Doubly Selective Fading Channels with CSI Uncertainty

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Abstract

To detect spatially-modulated signals, a receiver needs the channel state information (CSI) about each transmit-receive antenna pair. Although the CSI (or channel response information) is never perfect and varies in time, most studies on spatial modulation (SM) systems assume perfectly known CSI and time-invariant channel. The spatial correlations among multiple spatial subchannels, which have to be considered when CSI is imperfect, are also often neglected. In this paper, we release the above assumptions and take the CSI uncertainty and the spatial and temporal selectivities into account. We derive the channel estimation error-aware maximum likelihood (CEEJA-ML) detectors as well as several low-complexity suboptimal alternatives for PSK and QAM signals. As the CSI uncertainty depends on the channel estimator used, we consider two practical estimators in our derivations.

Numerical results obtained by simulations show that the CEEJA-ML detectors offer clear performance gain against conventional mismatched SM detector and, more importantly, the proposed suboptimal detectors incur negligible performance loss.

Index Terms

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A spatial modulation (SM), as it allows only one transmit antenna to be active in any transmission interval and exploits the transmit antenna index to carry extra information [1], is a low-complexity and spectral-efficient multi-antenna-based transmission scheme. Besides requiring no multiple radio frequency (RF) transmit chains, its low complexity requirement is also due to the fact that the receiver does not need complicated signal processing to deal with inter-spatial channel interference (ICI).

Most receiver performance assessments on multi-antenna systems assume that the channel state information (CSI) is perfectly known by the receiver (e.g., [1]). In practice, the CSI at the receiver (CSIR) is obtained by a pilot-assisted or decision-directed (DD) estimator [2] and is never perfect. The impacts of imperfect CSIR on some MIMO detectors were considered in [3]–[5] to evaluate the detectors’ performance loss. Furthermore, the channel is usually not static, especially in a mobile environment, but the channel-aging effect, i.e., the impact of outdated CSI, is neglected in most of these studies except for [5]. [6] discussed the effect of the channel coefficients’ phase estimation error; other earlier works on SM detection all employ the perfect CSI and time-invariant channel assumptions which thus yield suboptimal performance in realistic environments [7].

The difficulty in deriving the optimal SM detector in a doubly (time and space) selective fading channel with imperfect CSI is due to the fact that the likelihood function depends not only on the transmitted symbol but also the CSI estimator and its performance. Other works [8], [9] that consider imperfect CSI usually assume the estimation error covariance matrix is known, without regard to the estimator used. In this paper, we consider two MIMO channel estimators/trackers for a signal structure which inserts pilot symbols periodically among data blocks such that each frame consists of a pilot block and several data blocks. The first scheme treats the detected data as pilots to update channel estimate which is then used to detect the symbols of the following
data block. The second scheme describes the channel variation by a polynomial model so that channel estimation becomes that of estimating the polynomial coefficients using three consecutive pilot blocks. We refer to the first scheme as the DD estimator (tracker) and the second one the model-based (MB) estimator [10].

Our contributions are summarized as follows. We first derive a general channel estimation error-aware (CEEA) maximum likelihood (ML) receiver structure for detecting general MIMO signals in a doubly selective fading channel. The CEEA-ML detectors for $M$-PSK and $M$-QAM based SM systems are obtained by specializing to SM and PSK/QAM signal formats. As the ML detectors require high computational complexity, we then develop two classes of low-complexity suboptimal detectors. The first class detects the transmit antenna index and symbol separately while the second class simplifies the likelihood functions by using lower-dimension approximations, neglecting the spatial correlation on either the receive or transmit side. Both simplifications, separate detection and dimension reduction of the likelihood function, can be combined to yield even simpler detector structures. As will be seen later, the low-complexity detectors do not incur much performance loss.

The rest of this paper is organized as follows. In Section II we present a general system structure which includes the transmit MIMO signal, a generic space-time (S-T) channel model, and the corresponding detection rule based on perfect CSI. Both DD- and MB-based estimators are introduced as well. In Section III we focus on MB-based systems. A general CEEA-ML detector for general MIMO signals is first derived, followed by those for $M$-PSK and $M$-QAM SM signals. A low-complexity two-stage receiver for $M$-PSK SM systems is given at the end of the section. Section IV presents similar derivations for DD-based SM systems. In Section V we develop simplified CEEA-ML and two-stage detectors for both MB- and DD-based SM systems by using lower-dimension approximations of the likelihood functions. Because of space limitation, the presentation is concise, skipping most detailed derivations. The computational complexity and memory requirement of the mentioned detectors is analyzed in Section VI. As far as we know, materials presented in Sections III–V are new. The performance comparison of our and the conventional detectors is given in Section VII. Finally, we summarize our main
contributions and findings in Section VIII.

Notations: Upper and lower case bold symbols denote matrices and vectors, respectively. $I_N$ is the $N \times N$ identity matrix and $0_N$ the $N \times 1$ all-zero vector. $(\cdot)^T$, $(\cdot)^*$, $(\cdot)^H$, $(\cdot)^{-1}$ and $(\cdot)^\dagger$ represent the transpose, element-wise conjugate, conjugate transpose, inverse, and pseudo-inverse of the enclosed items, respectively. vec$(\cdot)$ is the operator that forms one tall vector by stacking the columns of a matrix. While $\mathbb{E}\{\cdot\}$, $|\cdot|$, and $\|\cdot\|_F$ denote the expectation, absolute value, and Frobenius norm of the enclosed items, respectively, $\otimes$ denotes the Kronecker product and $\odot$ the Hadamard product. $(\cdot)_i$ and $[\cdot]_{ij}$ respectively denote the $i$th row and $(i,j)$th element of the enclosed matrix. Diag$(\cdot)$ translates the enclosed vector or elements into a diagonal matrix with the nonzero terms being the enclosed items, whereas DIAG$(\cdot)$ is defined by

$$\text{DIAG}(x_1, x_2, \cdots, x_M) =
\begin{bmatrix}
x_1 & 0_{N_1} & \cdots & 0_{N_1} \\
0_{N_2} & x_2 & \cdots & 0_{N_2} \\
. & . & \ddots & . \\
0_{N_M} & 0_{N_M} & \cdots & x_M
\end{bmatrix}$$

with vector length of $x_i$ being $N_i$.

II. Preliminaries

A. S-T Correlated Channel

We consider a MIMO system with $N_T$ transmit and $N_R$ receive antennas and assume a block-faded scenario in which the MIMO channel remains static within a block of $B$ channel uses but varies from block to block. Thus, the received sample matrix of block $k$ can be expressed as

$$Y(k) \overset{def}{=} [y_1(k), \cdots, y_B(k)] = \mathbf{H}(k)\mathbf{X}(k) + \mathbf{Z}(k) \quad (1)$$

where $\mathbf{H}(k) = [h_1(k), \cdots, h_{N_T}(k)] \overset{def}{=} [h_{ij}(k)]$ is the $N_R \times N_T$ channel matrix, $\mathbf{X}(k) = [x_1(k), \cdots, x_B(k)]$ the $N_T \times B$ ($B \geq N_T$) matrix containing the modulated symbols carrying data or pilot signals, and the entries of matrix $\mathbf{Z}(k)$ are i.i.d. $\mathcal{CN}(0, \sigma^2_z)$ representing additive white Gaussian noise.
Let $\Phi = \mathbb{E}\{\text{vec}(H(k))\text{vec}^H(H(k))\}$ be the matrix whose $(N_R N_T)^2$ entries represent the mutual correlation coefficients amongst spatial subchannels.

$$\text{vec}(H(k)) = \Phi^{\frac{1}{2}}\text{vec}(H_w(k)),$$

where $H_w(k)$ is an $N_R \times N_T$ matrix with i.i.d. zero-mean, unit-variance complex Gaussian random variables as its elements. We assume that the spatial correlation matrix $\Phi$ is either completely or partial known to the receiver in our derivations of various detector structures. The effect of using estimated $\Phi$ is studied by computer simulation in Section [VII].

We further assume that the spatial and temporal correlations are separable [11], i.e.,

$$\mathbb{E}\{h_{ij}(k)h^*_{mn}(\ell)\} = \rho_S(i - m, j - n) \cdot \rho_T(k - \ell)$$

with $\rho_T(k - \ell) \equiv \mathbb{E}\{h_{ij}(k)h^*_{ij}(\ell)\}$ denoting the subchannel autocorrelation in time and

$$\rho_S(i - m, j - n) \equiv \mathbb{E}\{h_{ij}(k)h^*_{mn}(k)\} = [\Phi]_{(j-1)N_R+i, (n-1)N_R+m}$$

the spatial correlation. As mentioned before, when only the channel estimates are available, the likelihood function depends on these S-T correlations and so are the corresponding CEEA-ML detectors.

B. Detection of SM Signals with Perfect CSIR

Although a spatial multiplexing system such as BLAST [12] has a multiplexing gain, it requires high-complexity signal detection algorithms to suppress ICI. The SM scheme is an alternative which avoids the ICI-related problems by imposing the single active antenna constraint and compensates for the corresponding data rate reduction by using the transmit antenna index to carry extra information bits [1].

An $m$-bit/transmission SM system partitions the data stream into groups of $m = \log_2(MN_T)$ bits of which the first $\log_2 N_T$ bits are used to determine the transmit antenna and the remaining bits are mapped into a symbol in the constellation $A_M$ of size $M$, for the selected antenna to transmit. Since only one transmit antenna is active in each transmission, the $j$th column of $X(k)$
is of the form

\[ x_j(k) = [0, \cdots, 0, x_{\ell_j}(k), 0, \cdots, 0]^T, \quad (4) \]

where \( \ell_j \equiv \ell_j(k) \) is the active antenna index and \( x_{\ell_j}(k) \overset{\text{def}}{=} s_j(k) \in A_M \) is the modulated symbol transmitted at the \( j \)th symbol interval of the \( k \)th block. A transmitted symbol block \( X \) can thus be decomposed as \( X = LS \), where \( S = \text{Diag}(s), \ s = [s_1, \cdots, s_B]^T, \ s_j \in A_M, \) and \( L \) is the \( N_T \times B \) SSK matrix defined as

\[
[L]_{ij} = \begin{cases} 
1, & \text{if } i = \ell_j; \\
0, & \text{otherwise.} 
\end{cases}
\quad (5)
\]

We define \( \mathcal{X} \) as the set of all \( N_T \times B \) matrices whose columns satisfy \( (4) \). The average power

\[
\varepsilon_s \overset{\text{def}}{=} \frac{1}{B} \mathbb{E} \left\{ \|X(k)\|_F^2 \right\} = \frac{1}{B} \mathbb{E} \left\{ \text{tr} \left( X(k)X^H(k) \right) \right\}
\]

is equivalent to the average power of \( A_M \). Therefore, for \( j = 1, \cdots, B \), the \( j \)th column vector in \( (1) \) can be written as

\[ y_j(k) = h_{\ell_j}(k)s_j(k) + z_j(k). \quad (7) \]

Assuming perfect CSIR, i.e., \( \hat{H}(k) = H(k) \), and i.i.d. source, we have the ML detector

\[
\hat{X}(k) = \arg \max_{X \in \mathcal{X}} P \left( Y(k) | H(k), X \right) \quad (8)
\]

where

\[
P \left( Y(k) | H(k), X(k) \right) = (\pi \sigma_z^2)^{-N_T} \exp \left( -\frac{1}{\sigma_z^2} \|Y(k) - H(k)X(k)\|_F^2 \right).
\]

With \( L = \{1, \cdots, N_T\} \), (8) is simplified as

\[
\left( \hat{s}_j(k), \hat{\ell}_j(k) \right) = \arg \min_{(s, \ell) \in A_M \times L} \|y_j(k) - h_\ell s\|^2, \quad (9)
\]

for \( j = 1, \cdots, B \).
C. Tracking a Time-Varying MIMO Channel

We now describe the two simple pilot-assisted channel trackers (estimators) to be considered in subsequent discourse. The first one models the channel’s time variation as a polynomial while the second one is a DD estimator that treats the detected data symbols as pilots. The frame structure considered is depicted in Fig. 1 where a frame consists of a pilot block and $N-1$ data blocks with a total length of $NB$ symbol intervals. The choice of $N$ depends on the channel’s coherence time. For MB-based systems, we use three consecutive pilot blocks to derive the CSI for $2N+1$ consecutive blocks and detect the data symbols within the corresponding neighboring frame pair. The DD channel estimator uses the pilot block at the beginning of a frame to obtain a channel estimate for detecting the data of the next data block. This newly detected data block is then treated as pilots (called pseudo-pilots) to update the channel information for detecting the ensuing data block. This pseudo-pilot-based channel estimation-data detection procedure repeats until the last data block of the frame is detected and a new pilot block arrives.

Let the pilot block be transmitted at the $k_p$th block and denote the $N_T \times B$ pilot matrix by $X(k_p) = X_p$. The corresponding received block is

$$Y(k_p) = H(k_p)X_p + Z(k_p)$$

with the average symbol power given by $\varepsilon_p \overset{\text{def}}{=} \frac{1}{B} \|X_p\|_F^2$ and $X_p$ a unitary matrix. In particular, for SM systems, we assume that $B = N_T$ and $X_p = \sqrt{\varepsilon_p}I_{N_T}$.

1) MB Channel Estimation: For a single link with moderate mobility, it is reasonable to assume that the variation of the $(i,j)$th component of the channel matrix $H(k)$ in the sampling epochs, $\{k\}$, follows a polynomial law [10]

$$h_{ij}(k) = \alpha_{ij}(k)k^2 + \beta_{ij}(k)k + \gamma_{ij}(k).$$

Define the coefficient vector $\xi_{ij}(k) \overset{\text{def}}{=} [\alpha_{ij}(k), \beta_{ij}(k), \gamma_{ij}(k)]^T$. By collecting the received samples at three consecutive pilot locations $Y(k_p)$, $Y(k_p + N)$, $Y(k_p + 2N)$, we update the
estimate for $\xi_{ij}(k)$ every two frames via
\[
\hat{\xi}_{ij}(k_p) \overset{\text{def}}{=} \begin{bmatrix} \hat{\alpha}_{ij}(k_p) & \hat{\beta}_{ij}(k_p) & \hat{\gamma}_{ij}(k_p) \end{bmatrix}^T = T^{-1}(k_p) \tilde{y}_{ij}(k_p)
\] (12)
where
\[
T(k) \overset{\text{def}}{=} \begin{bmatrix} k^2 & k & 1 \\ (k + N)^2 & k + N & 1 \\ (k + 2N)^2 & k + 2N & 1 \end{bmatrix}, \quad \tilde{y}_{ij}(k_p) \overset{\text{def}}{=} \begin{bmatrix} y_{ij}(k_p) \\ y_{ij}(k_p + N) \\ y_{ij}(k_p + 2N) \end{bmatrix} = \begin{bmatrix} h_{ij}(k_p) \\ h_{ij}(k_p + N) \\ h_{ij}(k_p + 2N) \end{bmatrix} + \tilde{z}_{ij}(k_p),
\] (13a)
and $\tilde{z}_{ij}(k_p) \sim \mathcal{CN}(0, \sigma^2 z I_3)$. From (11) and (12) and define $t(k) = [k^2, k, 1]^H$, we obtain the estimates
\[
\hat{h}_{ij}(k) = t^H(k) \hat{\xi}_{ij}(k_p) = t^H(k) T^{-1}(k_p) \tilde{y}_{ij}(k_p)
\] (14)
for channel at blocks $k_p, \ldots, k_p + 2N - 1$.

2) Decision-Directed (DD) Channel Estimation: The DD channel estimator regards the detected data symbols in a data block as pilots to obtain an updated channel estimate and then use it for detecting the data symbols in the next data block. Error propagation, if exists, is terminated at the end of each frame as we start with a new channel estimate by using the new pilot block, i.e., the least squares (LS) estimate $\hat{H}(k_p + sN) \overset{\text{def}}{=} \hat{H}(k) = Y(k)\hat{X}^\dagger(k)$, $k = k_p + sN$, $s \in \mathbb{Z}$, to replace the old channel estimate.

We note that only one element in each column of the $k$th detected block $\hat{X}(k)$ is nonzero, hence it is likely that not all channel vectors $h_\ell(k)$’s are updated at each data block and $X(k)$ or $\hat{X}(k)$ is not of full rank most of the time. However, in the long run, all channel coefficients would be updated as each transmit antenna is equally likely selected. We denote by $\hat{H}[\mathcal{L}](k)$, the submatrix containing only the columns associated with the set of antenna indices activated in block $k$, $\mathcal{L} \subseteq \{1, \ldots, N_T\}$, i.e.

\[
\hat{H}[\mathcal{L}](k)(k) \leftarrow Y(k)\hat{X}^\dagger(k),
\]
where \( \hat{\Lambda}(k) \overset{def}{=} \{\hat{\ell}_1(k), \ldots, \hat{\ell}_B(k)\} \) and \( \bar{X}(k) \) is the truncated \( \tilde{X}(k) \) with its all-zero rows removed. By combining the submatrix which consists of those channel vectors estimated in the previous (the \((k - 1)\)th) block

\[
\hat{H}[L \setminus \hat{\Lambda}(k)](k) = \hat{H}[L \setminus \hat{\Lambda}(k)](k - 1),
\]

we obtain a full-rank channel matrix estimate \( \hat{H}(k) \).

**Remark 1:** As the DD method uses the channel estimate obtained in the previous block for demodulating the current block’s data symbols, error propagation within a frame is inevitable. The MB approach avoids error propagation at the cost of increased latency and storage requirement. Detailed computing complexity and memory requirement are given in Section VI.

**Remark 2:** The DD method updates the channel estimate in each block while the channel’s time variation is taken into account by the MB approach through the model (11) which leads to the estimate (14) in an \( N \)-block frame. For both channel estimators, the frame size \( N \) or equivalently, the pilot density is to be determined by the channel’s coherence time or fade rate.

### III. Channel Estimation Error-Aware ML Detection With MB Channel Estimates

As defined in [3], a *mismatched detector* is one which replaces \( H(k) \) in (8) by the estimated CSI \( \hat{H} \)

\[
\hat{X}^{\text{MM}}(k) \overset{def}{=} \arg\min_{X \in \mathcal{X}} \|Y(k) - \hat{H}X\|_F^2.
\] (15)

In our case, \( \hat{H} \) is either \( \hat{H}(k) \) or \( \hat{H}(k - 1) \) depending on whether an MB or DD estimator is used.

We extend the basic approach of [3] by taking the channel aging effect and the spatial correlation into account and refer to the resulting detectors as *channel estimation error-aware (CEEA)-ML detectors*. While most of the existing researches assume a time-invariant environment, we assume that the channel varies from block to block and is spatial/temporally correlated. As in [3] we need the following lemma in our ensuing analysis.
Lemma 1: \cite{13} Thm. 10.2] Let \( z_1 \) and \( z_2 \) be circularly symmetric complex Gaussian random vectors with zero means and full-rank covariance matrices \( \Sigma_{ij} \), \( \Sigma \) def = \( \mathbb{E}\{ z_i z_j^H \} \). Then, conditioned on \( z_2 \), the random vector \( z_1 \) is circularly symmetric Gaussian with mean \( \Sigma_{12} \Sigma_{22}^{-1} z_2 \) and covariance matrix \( \Sigma_{11} = \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \).

A. General MIMO Signal Detection with Imperfect CSI

When the MB channel estimate \( \hat{H}(k) \) is used, the CEEA-ML MIMO detector is given by

\[
\arg \max_{X \in A_{M+}} P \left[ \vec{Y}(k) \middle| \vec{X}, \vec{\hat{H}}(k) \right],
\]

where \( A_{M+} \) def = \( A_M \cup \{0\} \). Since the entries of \( Y(k) \) and \( \hat{H}(k) \) are all zero-mean random variables, invoking Lemma 1 with

\[
\begin{align*}
\mathbf{z}_1 &= \vec{Y}(k) = \left( X^T(k) \otimes I_{NR} \right) \vec{H}(k) + \vec{Z}(k), \\
\mathbf{z}_2 &= \vec{\hat{H}}(k) = \left[ \vec{Y}(k_p) \vec{Y}(k_p + N) \vec{Y}(k_p + 2N) \right] \left( t^H(k) T^{-1}(k_p) \right)^T,
\end{align*}
\]

for \( k_p < k < k_p + 2N \), gives

\[
\begin{align*}
\Sigma_{11} &= \mathbb{E}\{ \mathbf{z}_1 \mathbf{z}_1^H \} = \left( X^T(k) \otimes I_{NR} \right) \Phi X^*(k) \otimes I_{NR} + \sigma_z^2 I_{NRN_T}, \\
\Sigma_{12} &= \mathbb{E}\{ \mathbf{z}_1 \mathbf{z}_2^H \} = \mathbb{E}\{ \mathbf{z}_2 \mathbf{z}_2^H \} = \Sigma_{21}^H = t^H(k) T^{-1}(k_p) q(k) \left( X^T(k) \otimes I_{NR} \right) \Phi, \\
\Sigma_{22} &= \mathbb{E}\{ \mathbf{z}_2 \mathbf{z}_2^H \} = \nu(k) \Phi + \sigma_z^2 \left\| t^H(k) T^{-1}(k_p) \right\|_F^2 I_{NRN_T},
\end{align*}
\]

where

\[
\begin{align*}
q(k) &= \left[ \rho_T(k - k_p), \rho_T(k - k_p - N), \rho_T(k - k_p - 2N) \right]^T, \\
\nu(k) &= t^H(k) T^{-1}(k_p) \left[ \begin{array}{ccc}
1 & \rho_T(N) & \rho_T(2N) \\
\rho_T(N) & 1 & \rho_T(N) \\
\rho_T(2N) & \rho_T(N) & 1
\end{array} \right] \left( t^H(k) T^{-1}(k_p) \right)^H.
\end{align*}
\]

Direct substitutions of the above covariance matrices, we obtain from Lemma 1 the mean
vector \( \mathbf{m}_{mb}(k) \) and covariance matrix \( \mathbf{C}_{mb}(k) \)

\[
\mathbf{m}_{mb}(k) = (\mathbf{X}^T(k) \otimes \mathbf{I}_{N_R N_T}) \mathbf{A}(k) \text{vec}(\mathbf{H}(k)),
\]

(20a)

\[
\mathbf{C}_{mb}(k) = \sigma_2^2 \mathbf{I}_{N_R N_T} + (\mathbf{X}^T(k) \otimes \mathbf{I}_{N_R}) \left[ \mathbf{I}_{N_R N_T} - \mathbf{A}(k) \right] 

(t^H(k) \mathbf{T}^{-1}(k_p) \mathbf{q}(k))^* \Phi (\mathbf{X}^*(k) \otimes \mathbf{I}_{N_R})
\]

(20b)

for the likelihood function of \( \mathbf{Y}(k) \), where the spatial correlation \( \Phi \) also appears in

\[
\mathbf{A}(k) = t^H(k) \mathbf{T}^{-1}(k_p) \mathbf{q}(k) \Phi \mathbf{\Sigma}^{-1}_{22}.
\]

(20c)

For invertible \( \Gamma \in \mathbb{C}^{N_1 \times N_1} \) and arbitrary \( \chi \in \mathbb{C}^{N_1 \times N_2} \), we define

\[
\mathcal{G}(\Gamma, \chi) \overset{\text{def}}{=} \chi^H \Gamma^{-1} \chi
\]

(21)

and obtain from (16) a more compact form of the **CEEA-ML detector**

\[
\hat{\mathbf{X}}_{\text{ML}}(k) = \arg \min_{\mathbf{X} \in \mathcal{A}_{M}^{N_T \times B}} \mathcal{G} (\mathbf{C}_{mb}(k), \text{vec}(\mathbf{Y}(k)) - \mathbf{m}_{mb}(k)) + \log \det \mathbf{C}_{mb}(k).
\]

(22)

An alternate derivation of \( \Sigma_{11} \) and \( \Sigma_{12} \) begins with \( \hat{\mathbf{H}}(k) = \mathbf{H}(k) + \mathbf{E}(k) \). It is verifiable that

\[
\mathbb{E}\{\text{vec}(\mathbf{E}(k))\} = \mathbf{0}_{N_R N_T}
\]

and

\[
\Psi_E \overset{\text{def}}{=} \mathbb{E}\{\text{vec}(\mathbf{E}(k)) \text{vec}^H(\mathbf{E}(k))\} = \left( \nu(k) - 2 t^H(k) \mathbf{T}^{-1}(k_p) \mathbf{q}(k) + 1 \right) \Phi + \sigma_2^2 \left\| t^H(k) \mathbf{T}^{-1}(k_p) \right\|^2 F_{N_R N_T}.
\]

(23)

The received sample vector is thus related to \( \mathbf{E}(k) \) via

\[
\mathbf{Y}(k) = \hat{\mathbf{H}}(k) \mathbf{X}(k) + \left( \mathbf{Z}(k) - \mathbf{E}(k) \mathbf{X}(k) \right) = \hat{\mathbf{H}}(k) \mathbf{X}(k) + \tilde{\mathbf{Z}}(k),
\]

(24)

where \( \text{vec}(\tilde{\mathbf{Z}}(k)) \sim \mathcal{CN}(\mathbf{0}_{N_R N_T}, \sigma_2^2 \mathbf{I}_{N_R N_T} + \Psi_E) \). With

\[
\mathbf{z}_1 = (\mathbf{X}^T(k) \otimes \mathbf{I}_{N_R}) \text{vec}(\hat{\mathbf{H}}(k)) + \text{vec}(\tilde{\mathbf{Z}}(k)),
\]

we obtain \( \Sigma_{11} \) and \( \Sigma_{12} \) as given by (18a) and (18b).
A closer look at the components, (17a)–(20c), of the ML detector (22), reveals that the spatial correlation $\Phi$ affects the auto-correlations of the received signal and estimated channel, $\Sigma_{11}$ and $\Sigma_{22}$, and their cross-correlations, $\Sigma_{12}$ and $\Sigma_{21}$. The influence of the time selectivity $\rho_T(\cdot)$, frame structure (a pilot block every $N$ blocks), and estimator structure (14) on the latter three correlations can be easily found in (18b) and (18c) and through $q(k)$ and $\nu(k)$. These channel and system factors also appear in the estimator error covariance $\Psi_E$.

Remark 3: In contrast, in analyzing the performance of mismatched detectors and effects of imperfect CSI, [7]–[9] assume a simplified CSI error model that $E(k)$ consists only of white Gaussian components which are independent of the S-T correlations and channel estimator used, although the latter is a critical and inseparable part of the detector structure.

Remark 4: Equation (22) is general enough to describe detector structure for arbitrary data format and/or modulation schemes. For spatially-multiplexed (SMx) signals, the search range is modified to $A_M^{N_M \times B}$, while a precoded MIMO system, we replace $X$ by $WS$ with $W$ being the precoding matrix.

Specific detectors for various SM signals are developed in the ensuing sections.

B. CEEA-ML Detectors for SM Signals

1) M-PSK Constellation: With the decomposition $X = LS$ defined in Section II-B and $A_M$ an $M$-PSK constellation, the CEEA-ML detector for the PSK-based SM system is easily derivable from (22) and is given by

$$\hat{X}^{ML}(k) = \arg\min_{(s,L) \in A_M^{N_M \times L}} \log \det C_{psk}(k) + G(C_{psk}(k), y_s(k) - \bar{m}_{ssk}(k))$$

(25)

where $L$ denotes the set of all SSK matrices of the form (5) and $y_s(k) = \text{vec} \left( Y(k)S^H \right) / \varepsilon_s, \varepsilon_a = |s_j|^2$. $\bar{m}_{ssk}(k)$ and $\bar{C}_{psk}(k)$, which are not exactly the conditional mean and covariance, are obtained from (20a) and (20b) by substituting $L$ for $X$ and $\sigma_{x}^2$, for $\sigma_{z}^2$. In (25), we have defined, for an implicit function $f$ of $s$ and $L$,

$$\arg\min_{(s,L)} f(s, L) = \text{Diag}(\hat{s})\hat{L}, \ (\hat{s}, \hat{L}) = \arg\min_{(s,L)} f(s, L)$$

(26)
2) M-QAM Constellation: If $A_M$ is a square $M$-QAM constellation, the corresponding CEEA-ML detector is

$$
\hat{X}_{ML}(k) = \arg \min_{(s,L) \in A_M^B \times \mathcal{L}} N_R \log \det \mathbf{E}_s + \log \det \bar{C}_{qam}(k) \left[ \mathbf{y}_s(k) - \bar{m}_{ssk}(k) \right] \tag{27}
$$

with $\mathbf{E}_s \overset{\text{def}}{=} \mathbf{S}^H$, $\mathbf{y}_s(k) \overset{\text{def}}{=} \text{vec} \left( \mathbf{Y}(k) \mathbf{S}_H \mathbf{E}^{-1}_s \right)$, and

$$
\bar{C}_{qam}(k) \overset{\text{def}}{=} \sigma_z^2 \left( \mathbf{E}^{-1}_s \otimes \mathbf{I}_{N_R} \right) + \left( \mathbf{L}^T \otimes \mathbf{I}_{N_R} \right) \left[ \mathbf{I}_{N_R N_T} - \mathbf{A}(k) \left( \mathbf{t}^H(k) \mathbf{T}^{-1}(k_p) \mathbf{q}(k) \right)^* \right] \Phi \left( \mathbf{L}^* \otimes \mathbf{I}_{N_R} \right). \tag{28}
$$

C. Two-Stage $M$-PSK SM Detector

The SM detector calls for an exhaustive search over the set of all candidate antenna index-modulated symbol pairs, which has a cardinality of $|\mathcal{L} \times A_M|^B$. A low-complexity alternative which reduces the search dimension while keeping the performance loss to a minimum would be desirable. Toward this end, we consider a two-stage approach that detects the active antenna indices and then the transmitted symbols in each block. Similar approaches with perfect CSIR assumption have been suggested in [14].

We first notice that

$$
P \left[ \mathbf{Y}(k) \bigg| \mathbf{L}(k), \hat{\mathbf{H}}(k) \right] = \sum_{s_1(k)} \sum_{s_2(k)} \cdots \sum_{s_B(k)} P \left[ \mathbf{Y}(k) \bigg| \mathbf{L}(k), \mathbf{S}(k), \hat{\mathbf{H}}(k) \right] P \left[ \mathbf{S}(k) \right]
$$

where $\mathbf{L}(k)$ and $\mathbf{S}(k)$ are the $k$th block’s SSK and symbol matrices. It follows that the active antenna indices can be estimated by

$$
\hat{L}(k) = \arg \max_{\mathbf{L} \in \mathcal{L}} \frac{1}{M^B \sqrt{\det \varepsilon_s \bar{C}_{psk}(k)}} \sum_{s \in A_M^B} \mathcal{F}(s) \tag{29}
$$

where

$$
\mathcal{F}(s) \overset{\text{def}}{=} \exp \left[ -\mathcal{G}(\bar{C}_{psk}(k), \bar{m}_{ssk}(k)) - \frac{s^T \mathbf{J}(k) s^*}{2\varepsilon_s^2} + \frac{\Re \{ \mathbf{b}^H(k) s^* \} \varepsilon_s}{2} \right], \tag{30a}
$$

$$
\mathbf{J}(k) = \mathcal{G} \left( \bar{C}_{psk}(k), \text{DIAG}(\mathbf{y}_1(k), \cdots, \mathbf{y}_B(k)) \right), \tag{30b}
$$
\[ b(k) = \text{DIAG}(y_1(k), \ldots, y_B(k))^H \left( \bar{C}_{psk} \right)^{-1}(k) \bar{m}_{ask}(k). \]  

(30c)

Denote the solution of \( \partial \log F(s)/\partial s = 0 \) by \( \bar{s}(L) = \varepsilon_s(J^{-1}(k)b(k))^* \) and let \( Q_{A_M}(x) \) be the quantizer that maps each element of the vector \( x \) to its nearest constellation point in \( A_M \). For each candidate SSK matrix \( L \), we then use the approximation

\[ \sum_s F(s) \approx F(\bar{s}(L)), \quad \bar{s}(L) \overset{d}{=} Q_{A_M}(\bar{s}(L)) \]  

(31)

to obtain

\[ \hat{L}(k) \approx \arg \min_{L \in \mathcal{L}} \log \det(\varepsilon_s \bar{C}_{psk}(k)) + G(\bar{C}_{psk}(k), \bar{m}_{ask}(k)) + \frac{\bar{s}^T(L)J(k)\bar{s}(L)}{\varepsilon_s} - \frac{2\Re\{b^H(k)\bar{s}(L)\}}{\varepsilon_s}. \]  

(32a)

As mentioned in the previous subsection, \( \bar{C}_{psk}(k) \) and \( \bar{m}_{ask}(k) \) are both functions of \( L \), \( b(k) \) defined in (30c) is an implicit function of \( L \) and thus the approximation (31) depends on \( L \) and the associated tentative demodulation decision \( \bar{s}(L) \).

Once the active SSK matrix is determined, we output the decision \( \bar{s}(L) \) associated with \( \hat{L}(k) \) which has been determined in the previous stage

\[ \bar{s}(k) = \bar{s}(\hat{L}(k)). \]  

(32b)

(32b) will reappear later for several times, each with a different antenna index detection rule \( \hat{L}(k) \). For systems employing QAM constellations, the approximation (31) is not directly applicable as the nonconstant-modulus nature of QAM implies that \( F(s) \) has an additional amplitude-dependent term in the exponent.

IV. DD CHANNEL ESTIMATE-AIDED CEEA-ML DETECTORS

A. General MIMO Signal Detection with Imperfect CSI

To derive the CEEA-ML detector for general MIMO signals using a DD LS channel estimate, we again appeal to Lemma [1] with \( z_1 \) defined by (17a) and \( z_2 \overset{d}{=} \text{vec}(\bar{H}(k-1)) = \text{vec}(\bar{Y}(k-1)\hat{X}^H(k-1)) \). For \( k_p < k < k_p + N \), the signal block which maximizes the likelihood function
\[ P \left[ \text{vec}(\mathbf{Y}(k)) \left| \text{vec}(\mathbf{X}(k)), \text{vec}(\hat{\mathbf{H}}(k-1)) \right. \right] \text{ is given by} \]

\[
\hat{\mathbf{X}}_{\text{ML}}(k) = \arg \min_{\mathbf{X} \in \mathcal{A}_{M+}^{N_T \times B}} \log \det \mathbf{C}_{dd} + \mathcal{G}(\mathbf{C}_{dd}, \text{vec}(\mathbf{Y}(k)) - \mathbf{m}_{dd}). \tag{33}
\]

To have more compact expressions we use \(\hat{\mathbf{H}}\) and \(\hat{\mathbf{H}}(k-1)\) interchangeably for the DD CEEA-ML detectors. This is justifiable as the conditional mean and covariance of \(\mathbf{Y}(k)\) given \(\mathbf{X}(k)\) and \(\hat{\mathbf{H}}(k-1)\) are

\[
\mathbf{m}_{dd} = (\mathbf{X}^T(k) \otimes \mathbf{I}_{N_R}) \mathbf{A} \text{vec}(\hat{\mathbf{H}}(k-1)),
\]

\[
\mathbf{C}_{dd} = \sigma^2_z \mathbf{I}_{BNR} + (\mathbf{X}^T(k) \otimes \mathbf{I}_{N_R}) \left[ \mathbf{I}_{N_RN_T} - \rho_T(1) \mathbf{A} \right] \Phi \left( \mathbf{L}^* \otimes \mathbf{I}_{N_R} \right), \tag{34a}
\]

with \(\mathbf{A} \overset{\text{def}}{=} \rho_T(1) \Phi (\Phi + \sigma^2_z \mathbf{I}_{N_R})^{-1} \).

**B. CEEA-ML SM Signal Detectors**

Following the derivation of Section III-B and using the decomposition \(\mathbf{X} = \mathbf{L} \mathbf{S}\), we summarize the resulting DD CEEA-ML SM signal detectors for PSK and QAM constellations below.

1) **M-PSK Constellation:** For a PSK-based SM MIMO system, the CEEA-ML detector is expressed as

\[
\hat{\mathbf{X}}_{\text{ML}}(k) = \arg \min_{s_j \in \mathcal{A}_M, \ell_j \in \mathcal{L}} \log \det \tilde{\mathbf{C}}_{\text{psk}} + \mathcal{G}(\tilde{\mathbf{C}}_{\text{psk}}, \mathbf{y}_s(k) - \tilde{\mathbf{m}}_{\text{ssk}}) \tag{35}
\]

where \(\tilde{\mathbf{m}}_{\text{ssk}} = (\mathbf{L}^T \otimes \mathbf{I}_{N_R}) \mathbf{A} \text{vec}(\hat{\mathbf{H}})\) and \(\tilde{\mathbf{C}}_{\text{psk}} \overset{\text{def}}{=} \frac{\sigma^2_z}{\varepsilon^2} \mathbf{I}_{BNR} + (\mathbf{L}^T \otimes \mathbf{I}_{N_R}) \left[ \mathbf{I}_{N_RN_T} - \rho_T(1) \mathbf{A} \right] \Phi \left( \mathbf{L}^* \otimes \mathbf{I}_{N_R} \right).

2) **M-QAM Constellation:** As for M-QAM signals, (33) reduces to

\[
\hat{\mathbf{X}}_{\text{ML}}(k) = \arg \min_{s_j \in \mathcal{A}_M, \ell_j \in \mathcal{L}} N_R \log \det \mathbf{E}_s + \log \det \tilde{\mathbf{C}}_{\text{qam}} + \mathcal{G}(\tilde{\mathbf{C}}_{\text{qam}}, \mathbf{y}_s(k) - \tilde{\mathbf{m}}_{\text{ssk}}) \tag{36}
\]

where \(\tilde{\mathbf{C}}_{\text{qam}} \overset{\text{def}}{=} (\mathbf{L}^T \otimes \mathbf{I}_{N_R}) \left[ \mathbf{I}_{N_RN_T} - \rho_T(1) \mathbf{A} \right] \Phi (\mathbf{L}^* \otimes \mathbf{I}_{N_R}) + \sigma^2_z (\mathbf{E}_s^{-1} \otimes \mathbf{I}_{N_R}).\)

**Remark 5:** Compared with the MB channel estimator-aided detectors (cf. (25) and (27)), (35) and (36) require much less memory. The MB channel estimation is performed every two frames and thus \(2N - 2\) estimated channel matrices have to be updated and saved for signal detection.
The corresponding $A(k)$’s can be precalculated but they have to be stored as well. The DD channel estimator aided detectors, on the other hand, need to store two matrices, $A$ and $\hat{H}$, only. However, as shown in Section VII, the latter suffers from inferior performance. More detailed memory requirement comparison is provided in Section VI.

C. Two-Stage Detector for $M$-PSK SM Signals

We can reduce the search range of (35) from the $B$th Cartesian power of $L \times A_M$ to $L^B$ by adopting the two-stage approach of (32) that detects the antenna indices and then the transmitted symbols. The corresponding detector is derived from maximizing the likelihood function

$$P \left[ Y(k) \bigg| X(k), \hat{H}(k-1) \right]$$

with respect to $X(k)$:

$$\max_{L \in \mathcal{L}, s \in A_M^B} \left( \det \varepsilon_s \tilde{C}_{psk} \right)^{-\frac{1}{2}} \exp \left[ -\frac{s^T J(k) s^*}{2\varepsilon_s^2} + \frac{\Re \{ b^H(k) s^* \} \varepsilon_s}{2} \right]$$

$$\approx \max_{L \in \mathcal{L}} \left( \det \varepsilon_s \tilde{C}_{psk} \right)^{-\frac{1}{2}} \exp \left[ -\frac{\tilde{s}^T J(k) \tilde{s}^*(L)}{2\varepsilon_s^2} + \frac{\Re \{ \tilde{b}^H(k) \tilde{s}^*(L) \} \varepsilon_s}{2} \right],$$

(37)

where $J(k)$, $b(k)$, and $\tilde{s}(L)$ are defined similarly to those in (30b), (30c) and (31) except that now $\hat{H} = \hat{H}(k-1)$. Replacing the likelihood function by its logarithm version, we obtain a two-stage detector similar to (32) and (32b)

$$\hat{L}(k) = \arg \min_{L \in \mathcal{L}} \log \det (\varepsilon_s \tilde{C}_{psk}) + G(\tilde{C}_{psk}, \tilde{m}_{ssk}) + \frac{\tilde{s}^T (L) J(k) \tilde{s}^*(L) - 2\Re \{ \tilde{b}^H(k) \tilde{s}^*(L) \} \varepsilon_s}{\varepsilon_s^2},$$

(38a)

$$\hat{s}(k) = \tilde{s}(\hat{L}(k)).$$

(38b)

V. ML DETECTION WITHOUT RECEIVE SPATIAL CORRELATION INFORMATION

The detector structures presented so far have assumed complete knowledge of the channel’s spatial correlation $\Phi$. As pointed out in [11], when both sides of a link are richly scattered, the
corresponding spatial statistics can be assumed separable, yielding the Kronecker spatial channel model \[15\]

\[
H(k) = \Phi \frac{1}{2} H_w(k) \Phi \frac{1}{2}
\]

(39)

with the spatial correlation matrix \(\Phi\) given by

\[
\Phi = \Phi_T \otimes \Phi_R,
\]

(40)

the Kronecker product of the spatial correlation matrix at the transmit side \(\Phi_T = \mathbb{E}\{H^T(k)H^*(k)\}/\text{tr}(\Phi_T)\) and that at the receive side \(\Phi_R = \mathbb{E}\{H(k)H^H(k)\}/\text{tr}(\Phi_R)\). When the latter is not available, we assume that \(\Phi_R = I_{N_R}\) hence \(H(k) = H_w(k) \Phi \frac{1}{2}\). The assumption of uncorrelated receive antennas also implies

\[
P\left[ Y(k)|X(k), \hat{H}(k) \right] = \prod_{n=1}^{N_R} P\left[ y_n(k)|X(k), \hat{h}_n(k) \right],
\]

(41)

where \(y_n(k)\) is the sample (row) vector received by antenna \(n\) at block \(k\) and \(\hat{h}_n(k)\) the estimated channel vector between the \(n\)th receive antenna and transmit antennas. We will refer to a detector based on (41) as a zero-receive correlation (ZRC) detector.

A. MB Channel Estimate-Based ZRC Detector

1) General MIMO Detector: Define

\[
z_1^H = y_n(k) = h_n(k)X(k) + z_n(k),
\]

\[
z_2^H = \hat{h}_n(k) = t^H(k)T^{-1}(k)p\left[ \tilde{y}_{n1}(k_p), \tilde{y}_{n2}(k_p), \ldots, \tilde{y}_{nN_T}(k_p) \right]
\]

where \(Z(k) \overset{\text{def}}{=} [z_1(k), \ldots, z_{N_R}(k)]^T\). We immediately obtain the mean and covariance of \(y_n(k)\) conditioned on \(X(k)\) and \(\hat{h}_n(k)\) as

\[
m_n^{T}(k) = \hat{h}_n(k)A_{zrc}(k)X(k),
\]

(42a)

\[
C_{zrc}(k) = \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{12}^H = \sigma_z^2 I_{N_T} + X^H(k) \left[ I_{N_T} - A(k) \left( t^H(k)T^{-1}(k)pq(k) \right)^* \right] \Phi_T X(k),
\]

where \(A(k)\) is the channel estimate.
\[
A_{zrc}(k) = t^H(k)T^{-1}(k_p)q(k) \hat{\Phi} T \Sigma_{22}^{-1}, \quad \Sigma_{11} = X^H(k)\hat{\Phi}X(k) + \sigma_z^2 I_{N_T}, \quad \Sigma_{22} = \nu(k)\Phi_T + \sigma_z^2\|t^H(k)T^{-1}(k_p)\|^2_F I_{N_T}, \quad \text{and} \quad \Sigma_{12} = t^H(k)T^{-1}(k_p)q(k)X^H(k)\hat{\Phi}T \text{ with } q(k) \text{ and } \nu(k) \text{ being defined in (19).}
\]

The resulting **ZRC detector** is thus given by

\[
\hat{X}^{ZRC}(k) = \arg \min_{\bar{X} \in \mathcal{X}} N_R \log \det \mathcal{C}_{zrc}(k) + \text{tr} \left\{ G \left( \mathcal{C}_{zrc}(k), (Y(k) - \mathcal{M}_{zrc}(k))^H \right) \right\},
\]

where \( \mathcal{M}_{zrc}(k) = [\hat{m}_1(k), \ldots, \hat{m}_{m_R}(k)]^T = \mathcal{H}(k)A_{zrc}(k)X(k) \).

**Remark 6:** It is verifiable that (43) can also be derived from substituting \( \Phi_R = I_{N_R} \) into the CEEA-ML detection rule (22) and applying (40) with some additional algebraic manipulations. This is also applies for the DD channel estimate-aided counterpart.

On the other hand, when the spatial correlation at the transmit side is not available, we assume no a priori transmit spatial correlation, i.e., \( \Phi_T = I_{N_T} \). Substituting \( \Phi_T = I_{N_T} \) into (40) we obtain the **zero-transmit correlation (ZTC) detector** for a generic MB channel estimate-aided MIMO system with

\[
m_{mb}(k) = t^H(k)T^{-1}(k_p)q(k) \text{vec} \left( \Phi_R \left( \nu(k)\Phi_R + \sigma_z^2\|t^H(k)T^{-1}(k_p)\|^2_F I_{N_R} \right)^{-1} \mathcal{H}(k)X(k) \right),
\]

where we invoke \( X(k)X^H(k) \approx \varepsilon_s I_{N_T} \) to obtain the last equation with

\[
\bar{C}_{ztc}(k) \overset{d}{=} \sigma_z^2 I_{N_R} + \varepsilon_s \Phi_R \left( I_{N_R} - |t^H(k)T^{-1}(k_p)q(k)|^2 (\nu(k)I_{N_T} + \sigma_z^2\|t^H(k)T^{-1}(k_p)\|^2_F \Phi_R^{-1})^{-1} \right) \approx I_{N_T} \otimes \bar{C}_{ztc}(k),
\]

(44b)
As a result, 
\[ G(C_{mb}(k), \text{vec}(Y(k)) - m_{mb}(k)) = \text{tr} \left\{ G(C_{zte}(k), Y(k) - \bar{M}_{zte}(k)) \right\} \] and 
\[ \text{det} C_{zte}(k) = \text{det}^{N_T} \bar{C}_{zte}(k), \] where 
\[ \bar{M}_{zte}(k) = t^H(k)T^{-1}(k_p)q(k) \cdot \Phi_R \left( \nu(k)\Phi_R + \sigma^2_z \left\| t^H(k)T^{-1}(k_p) \right\|^2 \right) - \hat{H}(k)X(k). \] (46)

The resulting ZTC detector is given by 
\[ \hat{X}^{ZTC}(k) = \arg \min_{X \in A_{N_T \times B}} \text{tr} \left\{ G(\bar{C}_{zte}(k), Y(k) - \bar{M}_{zte}(k)) \right\} + N_T \log \text{det} \bar{C}_{zte}(k) \] (47)
which is of comparable computational complexity as that of the ZRC detector.

When both the transmit and receive correlations are unknown, the conditional covariance matrix in the detection metric degenerates to an identity matrix scaled by a factor that is a function of the noise variance, channel’s temporal correlation and block index k. Both ZRC and ZTC receivers can be further simplified by the two-stage approach, we focus on deriving reduced complexity ZRC detectors only; the ZTC counterparts can be similarly obtained.

2) Two-Stage ZRC M-PSK SM Detector: Following the derivation given in Section III-B we use the decomposition, \( X = SL \) and rewrite (43) for an M-PSK SM system as
\[ \hat{X}^{ZRC}(k) = \arg \min_{(s,L) \in A_{M}^{N_T \times L}} N_R \log \text{det}(\varepsilon_s \bar{C}_{ssk}(k)) + \text{tr} \left\{ G(\bar{C}_{ssk}(k), (Y_s(k) - \bar{M}_{ssk}(k))^H) \right\} \] (48)
where \( Y_s(k) = Y(k)S^H/\varepsilon_s \), \( \bar{M}_{ssk}(k) = \hat{H}(k)A(k)L \), and
\[ \bar{C}_{ssk}(k) = \frac{\sigma^2_s}{\varepsilon_s} I_{N_T} + L^H \left[ I_{N_T} - A(k)t^H(k)T^{-1}(k_p)q(k) \right] \Phi_T L. \] (49)

Decision rule for separate antenna index and modulated symbol detection can be shown to be given by
\[ \hat{L}(k) = \arg \min_{L \in L} N_R \log \text{det}(\varepsilon_s \bar{C}_{ssk}(k)) + \text{tr} \left\{ G \left( \bar{C}_{ssk}(k), (\bar{M}_{ssk}(k))^H \right) \right\} \] 
\[ + \frac{s^H(L)j(k)s(L)}{\varepsilon_s^2} - \frac{2\Re\{b^T(k)s(L)\}}{\varepsilon_s}, \] (50a)
\[ \hat{s}(k) = \bar{s}(\hat{L}(k)), \] (50b)
where \( \tilde{s}(L) = Q_{A_m}(\varepsilon_s(b^T(k)J^{-1}(k))^H) \), \( J(k) = C_{ssk}^{-1} \odot (Y^H(k)Y(k))^* \), and the entries of \( b(k) \) are the diagonal terms of \( Y^H(k)M_{ssk}C_{ssk}^{-1} \).

### B. DD Channel Estimate-Based ZRC Detector

#### 1) SM Signal Detector: Based on the same ZRC assumption and the fact that in a DD system \( X(k) \) is detected with the DD channel estimates obtained at block \( k - 1 \), we follow the procedure presented in the previous subsection with \( z_1^H = y_n^H(k) \) and \( z_2^H = \tilde{h}_n \odot \hat{h}_n(k-1) \) as the diagonal terms of \( Y \). To derive the ZTC detector \( \Phi_T \), to obtain the covariance matrices

\[
\begin{align*}
\Sigma_{11} &= X^H(k)\Phi_T X(k) + \sigma_z^2 I_B, \\
\Sigma_{12} &= \rho_T(1)X^H(k)\Phi_T G_1(k-1), \\
\Sigma_{22} &= G_1^H(k-1)\left[ \Phi_T + \sigma_z^2 X(k-1)X^H(k-1) \right]^{-1} G_1(k-1) \\
&\approx G_1^H(k-1)\left[ \Phi_T + \sigma_z^2 \varepsilon_s I_B \right] G_1(k-1).
\end{align*}
\]

(51a)

(51b)

It follows immediately that, given \( X(k) \) and \( \hat{h}_n(k-1), y_n(k) \) has mean \( z_2^H \Sigma_{22}^{-1} \Sigma_{12}^H = \tilde{h}_n(\Phi_T + \sigma_z^2/\varepsilon_s I_B)^{-1} \Phi_T X(k) \cdot \rho_T(1) \) and covariance matrix

\[
\tilde{C}_{zrc} \overset{\text{def}}{=} \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{12}^H = \sigma_z^2 I_B + X^H(k)\left[ I_{N_T} - \rho_T^2(1) \left( I_{N_T} + \sigma_z^2 \Phi_T^{-1} \right)^{-1} \right] \Phi_T X(k)
\]

(52)

where \( \rho_T(1) \) can be treated as a prediction term used to alleviate the error propagation effect. The corresponding ZRC detector is then given by

\[
\hat{X}^{ZRC}(k) = \arg\min_{X \in \mathcal{X}} N_R \log \det \tilde{C}_{zrc} + \text{tr} \left\{ \mathcal{G} \left( \tilde{C}_{zrc}, Y^H(k) - \tilde{M}_{zrc}^H \right) \right\},
\]

(53)

where \( \tilde{M}_{zrc} = \rho_T(1)\hat{H} \left( I_{N_T} + \sigma_z^2/\varepsilon_s \Phi_T^{-1} \right)^{-1} X(k) \). Similarly, this ZRC detector becomes the CEEA-ML detector when \( \Phi_R = I_{N_R} \).

To derive the ZTC detector for a DD channel estimate-aided MIMO system, we replace \( \Phi \) by \( I_{N_T} \otimes \Phi_R \) in \((34)\) and invoke

\[
A = \rho_T(1)(I_{N_T} \otimes \Phi_R)(I_{N_T} \otimes \Phi_R + \sigma_z^2 I_{N_RN_T})^{-1} = \rho_T(1) I_{N_T} \otimes \left( \Phi_R(\Phi_R + \sigma_z^2 I_{N_R})^{-1} \right)
\]

(54a)
and \( X(k)X^H(k) \approx \varepsilon_sI_{NT} \) to obtain the following:

\[
\mathbf{m}_{dd} = \text{vec} \left( \rho_T(1) \left( \Phi_R \Phi_R + \sigma_s^2 I_{NR} \right)^{-1} \tilde{H}X(k) \right) \overset{def}{=} \text{vec}(\tilde{M}_{ztc}), \quad (54b)
\]
\[
\mathbf{C}_{dd} \approx I_{NT} \otimes \left( \sigma_s^2 I_{NR} + \varepsilon_s \left( \Phi_R - \rho_T(1) \left( I_{NR} + \sigma_s^2 \Phi_R^{-1} \right)^{-1} \Phi_R \right) \right) \overset{def}{=} I_{NT} \otimes \tilde{C}_{ztc}. \quad (54c)
\]

The ZTC detector can be obtained as

\[
\tilde{X}^{ZTC}(k) = \arg\min_{X \in A_{MT}^{N_T \times B}} \text{tr} \left\{ G(\tilde{C}_{ztc}, Y(k) - \tilde{M}_{ztc}) \right\} + N_T \log \det \tilde{C}_{ztc} \quad (55)
\]

because in (33), \( G(\mathbf{C}_{dd}, \text{vec}(Y(k)) - \mathbf{m}_{dd}) = \text{tr} \left\{ G(\tilde{C}_{ztc}, Y(k) - \tilde{M}_{ztc}) \right\} \) and \( \det \mathbf{C}_{dd} \equiv \det_{NR} I_{NT} \cdot \det_{NT} \tilde{C}_{ztc} \).

2) Two-Stage ZRC M-PSK SM Detector: Let

\[
\tilde{M}_{ssk} = \rho_T(1)\tilde{H} \left( I_{NT} + \frac{\sigma_s^2}{\varepsilon_s} \Phi_R^{-1} \right)^{-1} L, \quad (56a)
\]
\[
\tilde{C}_{ssk} = \frac{\sigma_s^2}{\varepsilon_s} I_B + LH \left[ I_{NT} - \rho_T^2(1) \left( I_{NT} + \frac{\sigma_s^2}{\varepsilon_s} \Phi_R^{-1} \right)^{-1} \right] \Phi_R L. \quad (56b)
\]

Rewrite the ZRC detector for SM system with M-PSK symbols using DD channel estimates as

\[
\tilde{X}^{ZRC}(k) = \arg\min_{(s,L) \in A_{M}^{B} \times \mathbb{L}} N_R \log \det(\varepsilon_s \tilde{C}_{ssk}) + \text{tr} \left\{ G(\tilde{C}_{ssk}, \left( Y_s(k) - \tilde{M}_{ssk} \right)^H) \right\}. \quad (57)
\]

The corresponding two-stage ZRC detector can then be derived as

\[
\tilde{L}(k) = \arg\min_{L \in \mathbb{L}} N_R \log \det(\varepsilon_s \tilde{C}_{ssk}(k)) + \text{tr} \left\{ G(\tilde{C}_{ssk}, \left( \tilde{M}_{ssk} \right)^H) \right\}
+ \frac{s^H(L)J(k)s(L)}{\varepsilon_s^2} - \frac{2\Re \{ b^T(k)s(L) \}}{\varepsilon_s}, \quad (58a)
\]
\[
\tilde{s}(k) = \tilde{s}(\tilde{L}(k)), \quad (58b)
\]

where \( s(L) = Q_{AM} (\varepsilon_s (b^T(k)J^{-1}(k))^H), b(k) \) equals to the diagonal of \( Y^H(k)\tilde{M}_{ssk} \left( \tilde{C}_{ssk} \right)^{-1} \), and \( J(k) = \left( \tilde{C}_{ssk} \right)^{-1} \odot (Y^H(k)Y(k))^* \).

As the dimension of \( A_{ZRC}(k) \) for the ZRC detectors (43) and (48), \( N_T \times N_T \), is much smaller than that for the CEEA-ML detectors, \( N_RN_T \times N_RN_T \), the former class of detectors needs far less
memory space. The detail comparison of memory requirement and complexity of all detectors can be found in the next section.

VI. COMPLEXITY AND MEMORY REQUIREMENT OF VARIOUS SM DETECTORS

We now compare the computational complexity and memory requirement of the detectors derived so far. The memory space is used to store the required items involved in the detection metrics and is divided into two categories: i) fixed and ii) dynamic. The former stores the items that are independent of the received samples and/or updated channel estimates and can be calculated offline. The latter specifies those vary with the received samples. Take the ML detector \((22)\) for example. To achieve fast real-time detection, we pre-calculate and store \(C^{-1}_{mb}(k), \det C_{mb}(k)\) and \(m_{mb}(k)\) for all candidate signals \((X)\) and all \(k\) in two consecutive frames. These items are time-invariant, independent of \(Y(k)\) or \(\hat{H}(k)\). The dynamic part refers to the received samples (in two frames) which have to be buffered before being used to compute the MB channel estimate and detecting the associated signals. As \((X^T(k) \otimes I_{NR})A(k)\) for all candidate \(X\) can be precalculated and stored, the complexity to compute \((20a)\) is only \(O(M^{NTB}N_{RB}^{2}N_{T}^{2})\) complex multiplications per block. The remaining complexity is that of computing \(G(C_{mb}(k), \text{vec}(Y(k)) - m_{mb}(k))\).

As the CEEA-ML detector degenerates to the ZRC detector by setting \(\Phi = I_{NR}\), the dimensions of the correlation-related terms can be reduced by a factor of \(N_R\). This reduction directly affects both computing complexity and memory requirement. The complexity of the two-stage detector is only \(1/M^B\) of its single-stage counterpart because the parallel search on both transmit antenna index and data symbol has been serialized. However, the memory required remains unchanged.

For the mismatched detectors \((15)\), besides the dynamic memory to store \(\hat{H}\) and \(Y(k)\), the fixed memory, which consists mainly of those for storing the terms the channel estimators need, is relative small and usually dominated by the memory to store the statistics for the CEEA-ML detectors. A minimal complex multiplication complexity of \(O(M^{NTB}N_{RB}N_{T})\) is called for, since without channel statistics data of each channel use can be detected separately, i.e.,
\( \hat{X}^{MM}(k) \overset{def}{=} [\hat{x}_1^{MM}(k), \ldots, \hat{x}_B^{MM}(k)] \) with

\[
\hat{x}_j^{MM}(k) = \arg\min_{x \in \mathcal{A}_T} \| y_j(k) - \hat{H}x \|^2.
\]

The detectors using DD channel estimates need significantly less memory than those using MB ones as they do not jointly estimate the channel of several blocks and (33) indicates that \( C_{dd}^{-1} \) is independent of the block index. We summarize the computing complexities and the required memory spaces of various detectors in Tables I and II.

We conclude that, among all the proposed detectors, the ZRC (or ZTC) detectors are the most desirable as they require the minimal computation and memory to achieve satisfactory detection performance. Although the mismatched detector is the least complex and requires only comparable memory as ZRC (or ZTC) detectors do, its performance, as shown in the following section, is much worse than that of the proposed detectors in some cases.

VII. Simulation Results

In this section, the bit error rate (BER) performance of the detectors we have developed is studied through computer simulations. The pilot power \( \varepsilon_p \) is normalized to 1 for all cases and the performance of the mismatched detectors \([15]\) is provided for reference. We use the spatial channel model (SCM) \([11]\) and assume that uniform linear arrays (ULAs) are deployed on both sides of the link. The spatial correlation follows the Kronecker model \((39)\) so that (3) can be written as

\[
\rho_S(i - m, j - n) = [\Phi_T]_{jn} [\Phi_R]_{im} = \rho_S(0, j - n) \cdot \rho_S(i - m, 0).
\]

When the angle-of-arrivals (AoAs) and angle-of-departures (AoDs) are uniformly distributed in \((0, 2\pi)\), we have \([17]\)

\[
\rho_S(\ell - \ell', 0) = \rho_S(0, \ell - \ell') = J_0(2\pi(\ell - \ell')\delta/\lambda),
\]

where \( J_0(\cdot) \) is the zeroth-order Bessel function of the first kind, \( \delta \) the antenna spacing for both transmitter and receiver and \( \lambda \) the signal wavelength. This isotropic scattering scenario seldom occurs. Instead, if the AoAs and AoDs have limited angle spreads \([18]\), the spatial correlation
can be expressed as

$$\Phi_{R_{ij}} = r_{|i-j|}, \quad \Phi_{T_{ij}} = t_{|i-j|}$$

(60)

with $0 \leq r, t < 1$. The above exponential model has been widely applied for MIMO system evaluation [19] and proven to be consistent with field measurements [20]. We use both (60) and the isotropic model (59). As for time selectivity, we assume it is characterized by the well-known Jakes’ model [16]

$$\rho_T(k - \ell) = J_0(2\pi f_D(k - \ell)B_T s),$$

(61)

where $f_D$ is the maximum Doppler frequency and $T_s$ the symbol duration. The frame structure we consider is shown in Fig. 1 where a pilot block of the form $I_{N_T}$ (hence $B = N_T$) is placed at the beginning of each frame. The resulting pilot density is very low when compared with that of the cell-specific reference (CRS) signal in the 3GPP LTE specifications [21]. If we follow the symbol duration defined in [21], the pilot densities are only 1/6 and 1/3 of that used in 3GPP LTE. Unless otherwise specified, in the remainder of this section, we consider a $4 \times 4$ SM MIMO system with $M = 4$ and $B = 4$ to have a rate of 4 bits/transmission. If the pilot overhead is taken into account, the effective rate will be $(N - 1)/N$ of the nominal value.

A. MB Channel Estimator-Aided SM Detectors

The performance of MB based CEEA detectors is presented first. Figs. 2 and 3 shows the performance of the $\text{CEEA-ML}$ (25), $\text{mismatched}$ and suboptimal detectors as a function of $\bar{E}_b/N_0$, where $\bar{E}_b$ is the average received bit energy per antenna. The suboptimal detectors include the $\text{two-stage}$ (32), $\text{ZRC}$ (43), $\text{ZTC}$ (47), and the $\text{two-stage ZRC detectors}$ (50). While the ML and suboptimal detectors offer performance gain over the $\text{mismatched}$ one, the $\text{ZTC detector}$ suffers slightly more performance degradation against the $\text{CEEA-ML detector}$ than the $\text{ZRC}$ one does for it is obtained by using the additional approximation $X(k)X^H(k) \approx \varepsilon_sI_{N_T}$. The effect of spatial correlation can be found by comparing the two figures. When the spatial correlation follows (59) with $\delta = 1\lambda$, the channel correlation is relatively low and the knowledge of this correlation...
gives limited performance gain. But if the correlation is described by (60) with \( r = t = 0.5 \), the CEEL-ML and its low-complexity variations outperform the mismatched detector significantly, indicating the importance of CSI error awareness in highly correlated channel. Higher spatial correlation, on the other hand, causes larger performance loss for the ZRC and ZTC detectors which lack one side’s spatial information. The effect of shorter frame (\( N = 5 \)) is shown in Fig. 3 as well. As the channel estimate is improved by a higher pilot density, the performance gain becomes less impressive. Recall that, with perfect CSIR, the ML detector (8) does not need the channel’s spatial and/or time correlation information any more. This also implies that the performance gain is proportional to the CSI uncertainty.

From Table I, we find that the two-stage ZRC detector is the least complex one. Figs. 2 and 3 show its effectiveness: at BER = \( 5 \times 10^{-3} \), \( N = 10 \), although its performance loss against the ML detector is 4.5 dB for the high correlation channel \( r = t = 0.8 \) and the loss is less than 1 dB for \( r = t = 0.5 \). Using a higher pilot density \( N = 5 \), the loss is reduced to 0.2 dB for both channels. On the other hand, the two-stage detector, which requires slightly higher complexity, suffers only negligible degradation at the same BER.

The above results assume perfect correlation information is available, we consider the impact of imperfect correlation information in Fig. 4 where the time-averaged channel estimates over two consecutive frames are used as \( \Phi_T \) and \( \Phi_R \) (the temporal correlation is similarly estimated) in the ZRC and ZTC detectors. We notice that in this case, both detectors give similar performance when the spatial correlation is high \( (r = t = 0.8) \). Furthermore, even using only two blocks for correlation matrices estimation, both detectors maintain some performance gain over the mismatched counterpart. But the imperfect knowledge of channel statistics causes the ZRC and ZTC detectors, at BER = \( 2 \times 10^{-2} \), \( r = t = 0.8 \) to lose 2.5 and 0.3 dB performance gain (against the mismatched). However, if the spatial correlation decreases \( (r = t = 0.5) \), the loss at BER = \( 2 \times 10^{-3} \) becomes 0.5 and 0.7 dB. The performance gain can be recovered sequentially by accumulating more pilot blocks to improve correlation estimates. Recall that in a two-frame period the MB estimator uses only three pilot blocks.

As the spatial channel’s effective rank is a decreasing function of the spatial correlation, it
becomes more difficult for an SM detector to resolve spatial channels (different $h_j$’s) and the corresponding performance degrades accordingly. This holds for detectors with perfect CSIR and those using the MB or DD channel estimator. The neglect of CSI error and the correlation information causes more performance loss for channels with stronger correlations as can be found by comparing the mismatch losses in Figs. 2 and 3. Detectors with complete CSIR are unaffected by the channel’s time selectivity but with CSI error, performance degrades with larger $f_D T_s$ and/or smaller pilot density due to an increased CSI error.

**B. DD Channel Estimator-Aided SM Detectors**

Figs. 5 and 6 present the performance of the DD channel estimator aided detectors. As expected, the proposed detectors outperform the mismatched one. The effects of the pilot density, correlation level and other behavior of these detectors are similar to those observed in the previous subsection. Compared with the detectors using the MB channel estimator, the DD estimate-aided detectors are more sensitive to the CSIR error. This is because the latter uses the channel estimates of the previous block, which is likely to be outdated in a fast fading environment and any detection error will propagate until the next pilot block is received. The MB estimate-based detectors which use three consecutive pilot blocks to fit the time-varying channel response are thus immune to error propagation. Therefore, increasing the pilot density leads to more performance enhancement for the DD systems than for MB systems. Doubling the pilot density gives a 6 dB gain at $BER = 3 \times 10^{-2}$, $r = t = 0.8$ (or $BER = 1 \times 10^{-2}$, $r = t = 0.5$) for the ML-DD detector, in contrast to the 2 dB gain for the ML-MB detector. The ZRC and ZTC detectors ignores respectively receive and transmit spatial correlations, hence, it is only natural that their performance becomes closer to that of the CEEA-ML detector as the spatial channel decorrelates, i.e., as $r$ and $t$ become smaller.

**C. CEEA-ML Detection of SMX Signals**

We finally examine the performance of the SMX systems (Figs. 7 and 8) in S-T correlated channels using the CEEA-ML detector (22). The SMX system has the parameter values $B =$
$N_T = N_R = 2$ and $M = 4$ so that it yields the same 4 bits/transmission efficiency as before. These two figures reveal that the *CEE-ML detector* and its suboptimal derivatives also bring about performance gain against the *mismatched* one. However, the gain in the high-SNR regime where ICI is the dominant deteriorating factor is not as significant as that of SM detectors. When the spatial correlation is high, the performance is bounded by uniformly deep-fade cases (all $|h_i|$’s are small), yielding degraded averaged performance. Since SM signals do not suffer from ICI, the occasional single-channel fade has less severe impact on the BER performance. We present MB-based detectors’ performance only as the DD-based SMX detectors give even worse performance.

VIII. CONCLUSION

We have derived ML and various suboptimal detector structures for general MIMO (including SM and SMX) systems that take into account practical design factors such as CSI uncertainty, the channel’s S-T correlations, and the channel estimator used. The pilot-assisted MB and DD channel estimators we considered are simple yet efficient for estimating general correlated time-varying MIMO channels.

The suboptimal detectors are obtained by simplifying the ML detector’s exhaustive search process, the spatial correlation structure, the likelihood function, or a combination of these approximations. The complexities of the ML, suboptimal and mismatched detectors are analyzed. The effects of space and/or time selectivity and CSI uncertainty using practical channel estimators on the system performance are studied via simulated numerical examples with the performance of perfect CSIR detector used as a reference. We demonstrate how the CSI uncertainty affects various detectors’ BER performance and when the fading channel’s time or spatial selectivity has to be taken into consideration. The corresponding performance of spatial multiplexing system is provided as well. The numerical results also enable us to find the channel conditions and performance requirements under which the low-complexity suboptimal detectors incur only minor performance degradation.
REFERENCES

[1] M. Di Renzo, H. Haas, A. Ghrayeb, S. Sugiura, and L. Hanzo, “Spatial modulation for generalized MIMO: challenges, opportunities, and implementation,” Proc. IEEE, vol. 102, no. 1, pp. 56–103, Jan. 2014.

[2] S. K. Wilson, R. E. Khayata, and J. M. Cioffi, “16-QAM modulation with orthogonal frequency-division multiplexing in a Rayleigh-fading environment,” in Proc. IEEE VTC, vol. 3, pp. 1660–1664, Stockholm, Sweden, Jun. 1994.

[3] G. Taricco and E. Biglieri, “Space-time decoding with imperfect channel estimation,” IEEE Trans. Wireless Commun., vol. 4, no. 4, pp. 1874–1888, Jul. 2005.

[4] R. K. Mallik and P. Garg, “Performance of optimum and suboptimum receivers for space-time coded systems in correlated fading,” IEEE Trans. Commun., vol. 57, no. 5, pp. 1237–1241, May 2009.

[5] J. Zhang, Y. V. Zakharov, and R. N. Khal, “Optimal detection for STBC MIMO systems in spatially correlated Rayleigh fast fading channels with imperfect channel estimation,” in Proc. IEEE ACSSC, Pacific Grove, CA, Nov. 2009.

[6] M. Di Renzo, and H. Haas, “Space shift keying (SSK) modulation with partial channel state information: Optimal detector and performance analysis over fading channels,” IEEE Trans. Commun., vol. 58, no. 11, pp. 3196–3210, Nov. 2010.

[7] E. Başar, Ü. AYGÖLÜ, E. Panayircı, and H. V. Poor, “Performance of spatial modulation in the presence of channel estimation errors,” IEEE Commun. Lett., vol. 16, no. 2, pp. 176–179, Feb. 2012.

[8] R. Mesleh, O. S. Badarneh, A. Younis, and H. Haas “Performance analysis of spatial modulation and space-shift keying with imperfect channel estimation over generalized $\eta$-$\mu$ fading channels,” IEEE Trans. Veh. Technol., vol. 64, no. 1, pp. 88–96, Jan. 2015.

[9] O. S. Badarneh, R. Mesleh. (2015, Apr.). Performance analysis of space modulation techniques over $\alpha$-$\mu$ and $\kappa$-$\mu$ fading channels with imperfect channel estimation. Trans. Emerging Tel. Tech. [Online]. Available: http://dx.doi.org/10.1002/ett.2940.

[10] M.-X. Chang, “A new derivation of least-squares-fitting principle for OFDM channel estimation,” IEEE Trans. Wireless Commun., vol. 5, no. 4, pp. 726–731, Apr. 2006.

[11] C.-X. Wang, X. Hong, H. Wu and W. Xu, “Spatial-temporal correlation properties of the 3GPP spatial channel model and the Kronecker MIMO channel model,” EURASIP J. Wireless Commun. and Netw., 2007.

[12] G. J. Foschini, “Layered space-time architecture for wireless communication in a fading environment when using multi-element antennas,” Bell Labs Tech. J., vol. 1, no. 2, pp. 41–59, Sep. 1996.

[13] S. M. Kay, Fundamentals of Statistical Signal Processing, Volume I: Estimation Theory, Prentice Hall, 1993.

[14] C. Xu, S. Sugiura, S. X. Ng, and L. Hanzo, “Spatial modulation and space-time shift keying: optimal performance at a reduced detection complexity,” IEEE Trans. Commun. vol. 61, no. 1, pp. 206–216, Jan. 2013.

[15] J. P. Kermoal, L. Schumacher, K. I. Pedersen, and P. E. Mogensen, “A stochastic MIMO radio channel model with experimental validation,” IEEE J. Sel. Areas Commun., vol. 20, no. 6, pp. 1211–1226, Aug. 2002.

[16] W. C. Jakes, Microwave Mobile Communications, Wiley, 1974.

[17] M. Pätzold, B. O. Hogstad, and N. Youssef, “Modeling, analysis, and simulation of MIMO mobile-to-mobile fading channels,” IEEE Trans. Wireless Commun., vol. 7, no. 2, pp. 510–520, Feb. 2008.
TABLE I
MULTIPLICATION COMPLEXITIES PER DETECTED DATA BLOCK FOR VARIOUS DETECTORS WITH CONSTELLATION SIZE $M$, $\gamma_1 = M^{N_T}$, AND $\gamma_2 = M^B$.

| Detector      | General MIMO | SM | Two-stage |
|---------------|--------------|----|-----------|
| Mismatched    | $O(\gamma_1 B N_R N_T)$ | $O(M B N_R N_T)$ | N/A |
| CEEA-ML       | $O(\gamma_1^B N_R^2 N_T^2)$ | $O(\gamma_2^B N_R^2 N_T^2)$ | $O(N_R^{B+2} N_T^2)$ |
| ZRC           | $O(\gamma_1^B N_R N_T^2)$ | $O(\gamma_2^B N_R^2 N_T)$ | $O(N_R^{B+2} N_T)$ |

TABLE II
STORAGE REQUIREMENT (IN NUMBER OF COMPLEX NUMBERS) PER DATA BLOCK FOR VARIOUS DETECTORS, WHERE $\gamma = M^{N_T} B$, $N_R^B$, AND $M^B N_R^B$ FOR GENERAL MIMO, PSK-SM, AND QAM-SM SIGNALS, RESPECTIVELY.

| Detector      | MB channel estimates | DD channel estimates |
|---------------|----------------------|----------------------|
| Mismatched    | Fixed $O(N)$         | $O(N_R N_T)$         |
|               | Dynamic $O(N N_R N_T)$ | $O(N_R N_T)$         |
| CEEA-ML       | Fixed $O(\gamma N N_R^2 N_T^2)$ | $O(\gamma N_R^2 N_T^2)$ |
|               | Dynamic $O(N N_R N_T)$ | $O(N_R N_T)$         |
| ZRC           | Fixed $O(\gamma N N_T^2)$ | $O(N_R^2)$          |
|               | Dynamic $O(N N_R N_T)$ | $O(N_R N_T)$         |

[18] S. Bütükcörak and G. K Kurt, “Spatial Correlation and MIMO Capacity at 2.4 GHz,” in Proc. CIIECC 2012, Guadalajara, Mexico, May 2012.

[19] “Mobile and wireless communications enablers for the twenty-twenty information society (METIS); METIS channel models,” METIS Deliverable D1.4 V3, Jul. 2015. [Online]. Available: https://www.metis2020.com/documents/deliverables/

[20] D. Chizhik, J. Ling, P. W. Wolniansky, R. A. Valenzuela, N. Costa, and K. Huber, “Multiple-input-multiple-output measurements and modeling in Manhattan,” IEEE J. Sel. Areas Commun., vol. 21, no. 3, pp. 321–331, Apr. 2003.

[21] “Evolved universal terrestrial radio access (E-UTRA); physical channels and modulation,” 3GPP TR 36.211 V11.0.0, Oct. 2012. [Online]. Available: http://www.3gpp.org/ftp/Specs/html-info/36211.htm

Fig. 1. Signal structure of the SM system; pilot blocks are inserted periodically.
Fig. 2. Performance of SM detectors using an MB channel estimator in different environments; $N = 10, M = 4$, $N_T = N_R = B = 4$, and (Left) $\delta = 1\lambda$; (Right) $\delta = 5\lambda$.

Fig. 3. Effects of pilot density and spatial correlation on the performance of SM detectors using an MB channel estimator; $N = 5$ or 10, $M = 4$, $N_T = N_R = B = 4$, $f_D T_s = 0.0222$, and (Left) $r = t = 0.8$; (Right) $r = t = 0.5$.

Fig. 4. Performance of the ZRC and ZTC SM detectors using estimated spatial correlation and MB channel estimator; $N = 10$, $M = 4$, $N_T = N_R = B = 4$, $f_D T_s = 0.0222$, and (Left) $r = t = 0.8$; (Right) $r = t = 0.5$. 
Fig. 5. Effect of the spatial correlation on the performance of the DD channel estimator-aided SM detectors; $f_D T_s = 0.0222$, $N = 10$, $M = 4$, $N_T = N_R = B = 4$, and (Left) $r = t = 0.8$; (Right) $r = t = 0.5$.

Fig. 6. Effect of the spatial correlation on the performance of the DD channel estimator-aided SM detectors; $f_D T_s = 0.0222$, $N = 5$, $M = 4$, $N_T = N_R = B = 4$, and (Left) $r = t = 0.8$; (Right) $r = t = 0.5$.

Fig. 7. Effects of Doppler shift and spatial correlation on the performance of the MB channel estimator-aided ML and mismatched SMX detectors; spatial correlation follows (59), $N = 10$, $M = 4$, $N_T = N_R = B = 2$, and (Left) $\delta = 1\lambda$; (Right) $\delta = 5\lambda$.

Fig. 8. Performance of the MB channel estimator-aided SMX detectors in exponential-correlated channels; $N = 10$, $M = 4$, $N_T = N_R = B = 2$, $f_D T_s = 0.0222$, and (Left) $r = t = 0.8$; (Right) $r = t = 0.5$. 