Asynchronous Co-channel Interference Suppression in MIMO OFDM Systems

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Abstract—We present algorithms to suppress the asynchronous co-channel interference (CCI) in MIMO OFDM systems, which is becoming the dominant limiting factor in the performance of the emerging high-density WLANs. The key challenge is that the cyclic prefix of the interference signal does not line up with that of the intended signal due to asynchronous transmission in WLAN. Therefore, the orthogonality among the different tones of the interference signal is destroyed and conventional frequency domain minimum mean square error (MMSE) cancellation techniques that measure the interference channel response for each tone can not work effectively. To suppress the asynchronous interference, we design an efficient estimator to measure the interference spatial covariance matrix using Cholesky decomposition and low-pass smoothing. Both a MMSE and a maximum a posteriori (MAP) receiver are derived based on the estimated interference statistics. Simulation results demonstrate the effectiveness of our solution.

I. INTRODUCTION

Asynchronous co-channel interferences (CCI) is becoming the dominant performance limiting factor in emerging high-density WLAN (HD-WLAN)[6]. The problem is exacerbated when more and more access points (APs) are deployed in areas, such as office building, airport, university campus, etc., to provide network access for increasing number of mobile users. Only limited orthogonal channels (typically 3 or 8) are available. As a result, multiple cells that are operated on the same channel cannot be separated far enough and will interfere with each other if active at the same time. The next generation WLAN technology - 802.11n - combines orthogonal frequency division multiplex (OFDM) and multiple input multiple output (MIMO) techniques, providing good opportunities for achieving not only higher per-link throughput, but also better interference suppression capability.

Researchers have investigated the issue of CCI suppression extensively since Winters’s seminal paper [1]. The use of multiple antennas brings extra degrees of freedom for CCI suppression. [2] proposed a technique based on multiuser detection to cancel MIMO CCI for flat fading channels. Considering OFDM modulation and a time-varying channel, [3] designed an adaptive array processing scheme by using a MMSE diversity combiner. As pointed out in [4], the previous frequency domain approaches have difficulties in suppressing asynchronous interference, so they proposed a space-time filter to suppress CCI by utilizing the OFDM cyclic-prefix structure.

[5] is the most relevant to our work, which adopted a MMSE method and proposed to estimate the interference covariances for each subcarrier (or tone) by short training and utilizing the correlation among different tones. Besides the physical layer signal processing approaches, [6] designed a medium access control (MAC) based solution which adapts carrier sensing threshold to mitigate CCI from neighboring cells. It was shown by test-bed experiments that the proposed adaptive CSMA scheme can effectively address so-called “hidden and exposed terminal” problems and significantly improve network throughput.

Typically, CCI in a WLAN is asynchronous due to the use of a random access protocol, namely CSMA/CA (Carrier Sensing Medium Access/ Collision Avoidance). It was shown in [4] that the conventional frequency domain CCI cancellation by estimating both channels cannot work effectively because the cyclic padding OFDM modulation structure to maintain inter subcarrier orthogonality has been destroyed. Hence, we adopted a statistical methodology – modeling the asynchronous (co-channel) interference as a zero-mean, time uncorrelated and spatially colored Gaussian random process, and designed an efficient spatial covariance estimation algorithm by utilizing the OFDM symbol structure and matrix decomposition techniques. Simulation results show that our method can achieve packet error rate (PER) performance comparable to synchronized cancellation.

The rest of the paper is organized as follows. Section II describes the system model, and introduces the effect of asynchronous interference. An efficient spatial covariance estimation method for MIMO OFDM signals is proposed in Section III. In Section IV, the MMSE receiver enhanced with asynchronous CCI suppression capability is presented, as well as a modification for space-time coded systems is discussed. Then, the optimum MAP detector to minimize bit error probability is developed. Section VI shows the performance of our algorithms by extensive simulations. Finally, Section VII concludes.

Throughout this paper, normal letters indicate scalar quantities and boldface fonts denote matrices and vectors. For any matrix M we write its transpose as $M^T$ and $M^H$ is its conjugate transpose. $x^*$ denotes the conjugate of $x$. The superscript $k$ represents the $k$-th subcarrier.
II. System Model

Fig. 1 shows a MIMO OFDM system with $M$ transmitters and $N$ receivers. The encoded packet is interleaved and partitioned into $F$ blocks. Then the binary data blocks are mapped into $\{X(f,k)\mid 1 \leq f \leq F, 1 \leq k \leq K\}$ using the selected modulation, where $K$ is the number of subcarriers (tones). We denote $[X(f,1) \cdots X(f,K)]$ as one OFDM symbol. The OFDM symbols are space-time processed (through either space-time coded or spatial multiplexed), and then separated into $M$ groups. Each group is transmitted on one antenna. Before transmission, OFDM symbols are IFFT transformed into time domain and added cyclic prefix to minimize inter-symbol-interference (ISI) due to multi-path effect. The resulted transmission sequence is $\{x_i(n), i = 1 \cdots M\}$. We assume that the channel has $L$ taps, and keeps unchanged within a packet. The same channel model is used for both intended and interference signals. While, a random delay $\tau$ is introduced to model the asynchrony of interference. Finally, we can express the received signal at the desired user’s $j$th antenna as:

$$y_j(n) = \sum_{l=0}^{L-1} h_{i,j,l} x_i(n-l)$$

$$+ \sum_{u=1}^{M} \sum_{i=1}^{L-1} g_{i,j,l}^u z^u_l(n-l-\tau_u) + w_j(n), \quad (1)$$

where $h_{i,j,l}$ and $g_{i,j,l}^u$ define the the $l$th tap channel response for the desired transmitter and the $u$th interferer between the $i$th (transmit) antenna and the $j$th (receive) antenna, and $w_j(n)$ is the additive complex white Gaussian noise with zero mean and variance $N_0$. The second term in the above equation represents the co-channel interference.

Asynchrony destroys cyclic structure so that interference can no longer be modeled as the interferer’s channel on the given subcarrier multiplied by the data symbol. And, all the taps of the time-domain channel response will contribute to the interference for each tone. Now, take one interferer’s signal and denote as $q(n)$. For simplicity, we assume one transmit antenna case, extension to MIMO channel is straightforward. We rewrite the interference as cyclic structure according to the timing of desired signal [4].

$$q(n) = \sum_{l=0}^{L-1} g_l z([n-l]_K)$$

$$+ \sum_{l=0}^{L-1} g_l \{z(n-l) - z([n-l]_K)\} I_{(n-l)<0}, \quad (2)$$

where $K$ is the FFT size of circular convolution; $[n]_K$ means $n \mod k$, and the indicator function $I_{(n-l)<0}$ is one if $(n-l) < 0$ and zero otherwise. Basically, the interference signal is described as a circular convolutional term plus a correction term. Taking FFT of (2) gives:

$$Q(k) = G(k) Z(k) + \sum_{n=0}^{K-1} \sum_{l=0}^{L-1} g_l \{z(n-l) - z([n-l]_K)\}$$

$$\cdot I_{(n-l)<0} e^{-j2\pi kn/K}, \quad (3)$$

with $G(k)$ and $Z(k)$ being the $K$-point FFT of $g_l$ and $z(n)$ (for $0 \leq n \leq K-1$, respectively).

The second term of (3) implies we need $L$ degree of freedom to suppress the interference effectively by using the conventional MMSE receiver that estimates both the desired signal channel $h_l$ and the interference channel $g_l$.

III. Spatial Covariance Estimation for Asynchronous Interference

Instead of estimating the interference channel response, we model it as a zero mean, spatially colored Gaussian stationary random process for each tone. Hence, the second moment - covariance completely characterizes the statistics of interference. And, we proposed a statistical methodology to address the challenges of asynchronous CCI suppression. Gaussian modelling is not accurate, but it can provide useful statistical information to interference suppression. More important, Gaussian approximation is simple and easy for receiver design. The more the structure of the interference being exploited, the more effective the interference suppression algorithm is. We write the base-band received signal in the $k$th tone as follows:

$$Y^k(n) = H^k X^k(n) + I^k(n), \quad (4)$$

where $I(n) \in C^{N \times 1}$ represents interference plus noise, i.e., we lumped (3) and additive Gaussian noise into $I(n)$. The goal is to efficiently estimate the covariance of $I(n)$ in each tone, and then design the Wiener filter or the optimum MAP detector to suppress interference.

The spatial covariance of $I(n)$ in $k$th tone can be express as:

$$R_{ij}^k = E[I^k(n)^H I^i(n)] = \frac{1}{P} \lim_{P \to \infty} \sum_{n=0}^{P-1} \{I^k(n)^H I^i(n)\},$$

where $P$ is the training OFDM symbol number. However, it is not practical to measure the interference statistics for long time, and therefore a parsimonious spatial covariance estimator is proposed. First of all, we average limited samples to get the coarse estimation, which is the maximum likelihood estimation.
for each separated tone covariance. Then, we use the correlation information of OFDM tones to refine the estimation. Such correlation is inherent in the OFDM modulation structure and the multipath characteristics of fading channels. Moreover, we use the Cholesky decomposition method to turn a constrained parameter estimation problem (positive definite matrix) into an unconstrained one.

A. Temporal Low-Pass Smoothing

Let \( \tilde{R}^k_{ij} = \frac{1}{T} \sum_{n=1}^{P-1} \{ \tilde{I}^k(n) \tilde{I}^k(n)^H \} \), where \( \tilde{R}^k_{ij} \in \mathbb{C}^{N \times N} \). The matrix sequence \( \{ \tilde{R}^k_{ij} \} \) fully characterizes the statistics of the interference. The diagonal entries of the matrix sequence \( \tilde{S}_{mn} = \{ \tilde{R}^k_{ij}[n,n] \} \) are the estimated power spectral density (PSD) of signal from \( n \)th receive antenna. Similarly, the off-diagonal sequence \( \tilde{S}_{mn} = \{ \tilde{R}^k_{ij}[m,n] \} \) represents the estimate of mutual power spectral density between signal from the \( m \)th and \( n \)th antennas. We transform the auto/mutual PSD back to time domain with IFFT to get the cyclic auto/cross-correlation sequences.

\[
\tilde{r}_{mn} = F^{-1} \tilde{S}_{mn}, \quad m, n = 1 \cdots N,
\]

where \( F \) is a \( K \times K \) FFT matrix, \( \tilde{r}_{mn} \) denotes the correlation function.

We notice that the received signal is sum of the OFDM signals which have propagated through the multipath channels with an additive Gaussian white noise. Assume the original signals that output from each transmitter antennas are uncorrelated in time domain. Let the maximum delay tap of the multipath channel be \( L \). After the transmitted signal convoluted with the multi-tap channel response, two timing received samples will be correlated if separated less than \( L \), and uncorrelated otherwise,

\[
\tilde{r}_{mn} = \{ \tilde{r}_{mn}[0], \cdots, \tilde{r}_{mn}[L], 0, \cdots, 0, \tilde{r}_{mn}[K-L+1], \cdots, \tilde{r}_{mn}[K] \}
\]

Clearly, the correlation function has “low-pass” property, which will be exploited to smoothing the estimation. We null the terms for \( L < k < K-L+1 \) as shown in (7) before transforming \( \tilde{r}_{mn} \) back to frequency domain.

\[
\hat{r}_{mn} = D \tilde{r}_{mn}, \quad D = \text{diag}(d_k),
\]

\[
d_k = \left[ 1, \cdots, 1, 0, \cdots, 0, 1, \cdots, 1 \right].
\]

Hence, we get the smoothed spatial covariances estimations as

\[
\hat{S}_{mn} = F \hat{r}_{mn} = FDF^H \tilde{S}_{mn} = P \tilde{S}_{mn}.
\]

B. Cholesky Decomposition

In the area of multivariate statistics, it is a common approach to decompose the complicated matrixes into simpler components for further processing. There are three popular methods to use for matrix decomposition: variance-correlation decomposition, spectral decomposition (singular value decomposition (SVD)) and Cholesky decomposition. While the entries of the correlation and orthogonal matrices in the variance-correlation and spectral decompositions are still constrained, those in the lower triangle matrix of the Cholesky decomposition are always unconstrained. As a result, it becomes a smoothed refinement if smoothing the Cholesky decomposition of spatial covariance across different tones instead of the covariance itself as in previous section, and the Hermitian and positive definite structure can be maintained. The low-triangle matrix of the Cholesky decomposition provides sufficient statistics for the covariance estimation, and can be written as:

\[
\tilde{R}^k_{ij} = (U^k)^H \cdot U^k,
\]

where \( U^k \) is a upper triangle matrix, \( U^k \) is also called “square-root” of matrix \( \tilde{R}^k_{ij} \).

Instead of filtering the entry vectors of \( \tilde{R}^k_{ij} \), we now smooth that of upper triangle matrices \( U^k \). After the smoothing, we reconstruct the spatial covariance for each tone as \( \tilde{R}^k_{ij} = (U^k)^H \cdot U^k \). Since the correlation among different tones still maintain for square-root matrix \( U \), we can use the filtering matrix \( P \) in equation (8). Other choice of smooth function might be possible, e.g., Kaiser-Bessel window. In our case, we observed that the matrix \( P \) provides good performance with wise choice of \( L \).

The Cholesky decomposition method has been used in [7] for simultaneous estimation of several covariance matrix. It was also shown that the estimation of a covariance matrix is equivalent to estimating a sequence of varying-coefficient and varying-order regression models with unconstrained coefficients.

IV. INTERFERENCE AWARE RECEIVER DESIGN

The enhanced parsimonious spatial covariance algorithm proposed the above allows for better estimation of the statistics of asynchronous co-channel interference. In this section, we will design an interference-aware receiver to suppress CCI by utilizing the estimated statistics. First, we use the classical Wiener filter, i.e., MMSE. Due to similarity of receiver design across tones, in the following sections we omit the tone index - superscript \( k \).
TABLE I
SPATIAL COVARIANCE ESTIMATION ALGORITHM I

1. Samples Average Estimation: for \( k = 1 \cdots K \), \( \mathbf{R}_{II}^{k} = \frac{1}{T} \sum_{n=0}^{T-1} \{ \mathbf{I}^{k}(n) \mathbf{I}^{k}(n)^{H} \} \)
2. Cholesky Decomposition: for \( k = 1 \cdots K \), \( \mathbf{R}_{II}^{k} = (\hat{\mathbf{U}}^{k})^{H} \cdot \hat{\mathbf{U}}^{k} \)
3. Smoothing: For each entry in \( \hat{\mathbf{U}}^{k} \), let \( \hat{\mathbf{u}} = [\mathbf{U}^{1}[m,n] \cdots \mathbf{U}^{K}[m,n]]^{T} \), \( \mathbf{v} = \mathbf{P} \cdot \hat{\mathbf{u}} \),
   then \( \mathbf{v} = [\hat{\mathbf{U}}^{1}[m,n] \cdots \hat{\mathbf{U}}^{K}[m,n]]^{T} \), construct \( \hat{\mathbf{U}}^{k} \) from \( \mathbf{v} \).
4. Reconstructing: Reconstruct the estimated covariance: \( \mathbf{R}_{II}^{k} = (\hat{\mathbf{U}}^{k})^{H} \cdot \hat{\mathbf{U}}^{k} \).

A. MMSE Receiver for Co-channel interference mitigation

Denote the MMSE filter as \( \mathbf{W} \),
\[
\mathbf{W} = \mathbf{R}_{yy}^{-1} \mathbf{R}_{xy}^{H} ,
\]
where \( \mathbf{R}_{yy} = \mathbb{E}\{ \mathbf{x}(n)\mathbf{y}(n)^{H} \} = \mathbf{H} \), and \( \mathbf{R}_{xy} = \mathbb{E}\{ \mathbf{y}(n)\mathbf{y}^{H}(n) \} \). In order to obtain the MMSE filter, we need to estimate the channel of desired signal \( \mathbf{H} \) and the covariance of received signal \( \mathbf{R}_{yy} \). The simplest way to estimate \( \mathbf{R}_{yy} \) is to average the received signal vectors over a period of time. However, such method does not explore the structure of the received signal efficiently and can not provide accurate covariance estimation even with long-time average, especially for high-order modulations. Our simulation results have verified this argument (not shown in this paper due to limited space) and show poor performance of 16QAM or above. Due to the independence among desired signal, interference and noise. We can rewrite the covariance of the received signal as:
\[
\mathbf{R}_{yy} = \mathbf{HH}^{H} + \mathbf{R}_{II} .
\]

For the synchronous case, we have \( \mathbf{R}_{II} = \mathbf{G}\mathbf{G}^{H} + N_{0}\mathbf{I}_{N} \), where \( \mathbf{I}_{N} \) denotes the identity matrix and \( \mathbf{G} \) indicates the channel response of interference. For the asynchronous case, we will use the algorithm proposed in the previous section to estimate \( \mathbf{R}_{II} \). The receiver structure is shown in Fig. 2.

B. Enhancements for Space-time Block Coded (STBC) System

Space-time coding has recently emerged as a powerful approach to exploit the spatial diversity and combat fading in MIMO wireless communications systems.

For simplicity, we use the Alamouti code as an example, which has been adopted as one option by the next generation WLAN standard, e.g. 802.11n, and the analysis can be easily extended to other OSTBC. Modify the signal model in (4) to incorporate the space-time code. We can rewrite the received signal as:
\[
\begin{pmatrix}
y_{1}(n) \\
\vdots \\
y_{N}(n) \\
y_{1}(n+1) \\
y_{N}(n+1)
\end{pmatrix} =
\begin{pmatrix}
h_{11} & h_{12} \\
h_{21} & h_{22} \\
h_{N1} & h_{N2}
\end{pmatrix}
\begin{pmatrix}
x_{1} \\
x_{2}
\end{pmatrix}
+ \begin{pmatrix}
I_{1} \\
\vdots \\
I_{N} \\
I_{N+1} \\
I_{2N}
\end{pmatrix}
\]

Basically, we stacked the received signal vectors from time \( n \) and \( n+1 \) as one vector. \( \mathbf{I} \) is the asynchronous co-channel interference, which is a space-time coded signal plus noise. If the intended and interference signals are synchronized (both for OFDM cyclic structure and orthogonal space-time modulation), we will have \( 2N-2 \) extra degree freedom. However, for random asynchronous interference, the term \( \mathbf{I} \) is unstructured. Not only the degree of freedom is insufficient, but also we need double the dimension of the “spatial-temporal” covariance estimation. And even with the improved covariance estimation techniques in the previous section will not be able to provide good CCI suppression performance. Intuitively, it can be explained as the result of asynchrony making the space-time coded CCI acts as if we have a \( 2N \times 2N \) interference MIMO spatial multiplex transmission. Unfortunately, we only have \( 2N \) degree of freedom all together at the receiver, hence it is impossible to suppress the interference signal effectively.

Here, we propose a heuristic solution that is to block diagonalize the covariance matrix by zero-forcing the cross correlation information between two successive receive signal vectors from time \( n \) and \( n+1 \). The assumption is that these two signal vectors are separated far enough to be treated independently. More precisely, we write \( \mathbf{R}_{II} \) can be write as:

\[
\mathbf{R}_{II} = \begin{pmatrix}
\mathbf{R}_{II}(n) & 0 \\
0 & \mathbf{R}_{II}^{*}(n+1)
\end{pmatrix}
\]

Such process not only reduces the amount of estimation parameters by half, but also saves degree of freedom. The covariance matrix \( \mathbf{R}_{II}(n) \) and \( \mathbf{R}_{II}^{*}(n+1) \) can be estimated as previous by matrix decomposition and smoothing. Finally, for space-time codes system, we can use the MMSE receiver to suppress the interference by treat the STBC as an equivalent spatial multiplexing transmission with channel matrix as \( \mathbf{H} \).
C. MAP Receiver for Co-channel Interference Suppression

Since we have model the interference as Gaussian random process with zero mean and covariance $R_{II}$, we can derive the optimum MAP bit interleave to minimize bit error probability. Let’s assume a block of $M \log_2 C$ bits $b$ have been transmitted per channel use for each tone, where $C$ is the modulation constellation size. The a posteriori log-likelihood ratio value (L-value) of bits $b_i, i = 0, \cdots, M \log_2 C - 1$, conditioned on the received vector $y$ is

$$L_D(b_i|y) = \ln \frac{P(b_i = +1|y)}{P(b_i = -1|y)}.$$  \hfill (14)

Assuming the $\{b_i\}$ are independent due to the random interleave, (14) can be further expressed as:

$$L_D(b_i|y) = L_A(b_i) + \ln \sum_{x \in X_{b_i+1}} P[y|x] \cdot e^{\sum_{j \in J_{i,x}} L_A(b_j)},$$  \hfill (15)

where $X_{b_i+1}$ is the set of $2^M \log_2 C - 1$ bit vectors $x$ having $b_i = +1$, $X_{b_i-1}$ is the set of $2^M \log_2 C - 1$ bit vectors $x$ having $b_i = -1$ and $L_A(b_j) = -\ln P(b_j|y)$, is the a priori L-value. $J_{i,x}$ is the set of indices $j$ with

$$J_{i,x} = \{ j | j = 0, 1, 2, N_i M - 1, j \neq i, b_j = 1 \}. \hfill (16)$$

The second term on the RHS of (15) is the extrinsic L-value, defined as $L_E(b_i|y)$ and used below. The sets $X_{b_i+1}$ and $X_{b_i-1}$ can be either generate by exhaustive listing for small antenna number and lower modulation order, or generate by the list sphere decoding for large antenna number and higher order modulation [9].

To compute the L-value (15) for the MAP detector, one essential step is to compute the likelihood function $P[y|x]$, this can be found from the linear model of (4) and the estimated $R_{II}$

$$P[y|x] = \frac{1}{\pi^N \det(R_{II})} \exp[\langle y - Hx \rangle^H R_{II}^{-1} \langle y - Hx \rangle]$$

$$= \frac{1}{\pi^N \det(R_{II})} \exp\left[\|\hat{U}^{-1}(y - Hx)\|^2\right], \hfill (17)$$

where $\hat{U}$ is the Cholesky decomposition of the $R_{II}$. Using the max-log approximation, the extrinsic L-value can be approximated as

$$L_E(b_i|y) \approx \max_{x \in X_{b_i+1}} \left\{ -\frac{\|\hat{U}^{-1}(y - Hx)\|^2}{N_0} + \frac{1}{2} b_{[i]}^T L_{A,[i]} \right\}$$

$$- \max_{x \in X_{b_i-1}} \left\{ -\frac{\|\hat{U}^{-1}(y - Hx)\|^2}{N_0} + \frac{1}{2} b_{[i]}^T L_{A,[i]} \right\}, \hfill (18)$$

where $b_{[i]}$ denotes the sub-vector of $b$ omitting its $i^{th}$ element, and $L_{A,[i]}$ is the vector of all $L_A$ values, also omitting its $i^{th}$ element. The MAP detector can output soft information and iterative (Turbo) exchange the extrinsic information with outer channel decoder to improve the performance. The complexity of the MAP detector is higher than the MMSE receiver. Basically, the square-root matrix $U$ act as a pre-whitening filter to whiten the interference signal. Hence, an accurate spatial covariance estimation is also desirable for MAP detector.

V. SIMULATION RESULTS

In this section, we provide simulation results to show the effectiveness of proposed spatial covariance estimation algorithms and the CCI suppression receiver. An OFDM system of $K = 64$ subcarriers and $N_{sp} = 16$ samples cyclic prefix is considered. A rate 1/2 LDPC code of length 1944 bits is used, which has been adopted by 802.11n standard. Gray mapping is used for transmitted symbol modulation. Our performance metric is packet error rate (PER). Packet size is fixed as 972 bytes. A standard OFDM symbol level interleaver is used to combat frequency selectivity for the indoor multipath scattering channel. For simplicity, we assume the desired signal and interference use the same transmission setup. The interference is asynchronous with a offset uniformly distributed within one OFDM symbols (1 – 80 time samples).

The IEEE802.11n channel model D is used in our simulation. For the desired signal, we assume there is a line-of-sight (LOS) component in the first tap. But for interference signal, which usually located faraway (distance > 10m ‘breakpoint’), it only has NLOS path. The LOS path of the desired signal has an angle-of-arrival (AOA) of $\pi/4$. We assume one dominant co-channel interferer exists (For most situations, 1 – 2 strong interferers are typical). We estimated the interference at the beginning of the packet decoding with zero-padding $P$ OFDM symbols during transmission (i.e., the $P$ OFDM symbols consist of only interference and noise). Spatial covariances are parsimonious estimated by these $P$ OFDM symbols.

We first assume $1 \times 2$ SIMO case. For which APs have legacy one transmitter antenna, but the mobile terminals have two receive antennas. Fig. 5 compares different receiver schemes. The SNR value is fixed for 20 dB. The desired signal’s channel is estimated under the interference environment using one OFDM training symbols by the method in [8]. Note that for SIR larger than 5 dB, channel estimation can achieve the required accuracy for most cases. 4 OFDM symbols zero-padding duration are used to estimate the spatial covariance. From the plot, we can observe 8 dB gain in SIR compared to MRC receiver for PER of $10^{-2}$. The tone smoothing provides 1 dB gain and cholesky decomposition provides further 2 dB gain compared with the MMSE receiver without covariance estimation refinement. As a benchmark, the MMSE receiver with synchronized and perfect known interferer’s channel ($G$) is also plotted - dot line in the figure. Interestingly, there is less than 2dB gap between our proposed method and the synchronized case.

In Fig. 6., high-order modulation 64QAM is used for different receiver schemes. 64QAM is the worst for estimating the spatial covariance. The proposed algorithm still can provide a 6.5 dB gain compared with MRC receiver for PER of $10^{-2}$. For 64QAM modulation, covariance smoothing can provided 3 dB gain compared with non-smoothing MMSE, and the Cholesky decomposition improves the PER curve by
a further 2 dB gain. Again, the channel is estimated under the co-channel interference. Surprisingly, our proposed scheme perform even better than the synchronous curve - dot line.

Next, we consider the space-time coded transmission system. We use the Alamouti code with 2 transmitter antennas and 3 received antennas. We compared the PER of block diagonalized scheme and without the diagonalization. 6 OFDM symbols are used to zero pad for diagonalized case and 12 OFMD symbols for undiagonalized MMSE receiver in the covariance estimation. As we pointed out, MMSE without diagonalization have freedom deficiency problem, which deteriorates the MMSE receiver performance. With diagonalization of $R_{ff}$, the proposed the algorithm approach the synchronized, interference channel perfect know curve (dotted curve). Noticeably, MRC has better diversity gain, though the proposed the scheme provided 6 dB gain in SIR for PER of $10^{-2}$. Therefore, the interference suppression will sacrifice the diversity gain of the space-time code. Also, from the Fig. 5., we notice that the diversity gain of synchronized interference case is better than asynchronous interference mitigation. We further demonstrate CCI suppression for space-time coded system in Fig. 6. with 64QAM modulation.

We plotted the MAP decoder with/without iteration and compared with the MMSE receiver in Fig. 7. In order to eliminate the effect of channel estimation for low SIR. We assume the perfect channel knowledge of the desired signal. And 6 zero-padding OFDM symbols are used for interference statistics estimation. The MAP demodulator and LDPC decoder iterative exchange the extrinsic information. The iteration can provide a marginal gain of 1 dB compared with the MAP soft output demodulator. If the packet is successfully decoded, then the iterative process will be abort. By doing so, the receiver runs 1 – 2 iterations for most cases. Apparently, the MAP demodulator provides more diversity gain in contrast to MMSE receiver. Surprisingly, without matrix decomposition, the smoothed MMSE perform even worse than the conventional MMSE. This can be explained as the result of the smoothing (low-pass filtering) destroys the covariance matrix structure, especially for larger matrix size (4 receiver antennas).
VI. CONCLUSION

We have presented an efficient spatial covariance estimation method for MIMO OFDM system. The proposed method consists of a Cholesky decomposition step and a smoothing operation across OFDM tones. The algorithm can significantly improve the performance of an interference-aware receiver, demonstrated by the SIR gains for PER curves. We also designed the MMSE and MAP receiver based on the proposed interference statistic estimation method. The MAP receiver achieves better performance but at cost of higher complexity, compared with the MMSE one.

In the future work, we will apply our schemes to high density WLAN, where we should consider partial interference and the “capture” effect. In other word, only part of the packet is interfered by CCI, hence there is a statistics “mismatch” problem. One potential solution to investigate is zero-padding in multiple positions and partitioning the packet into smaller blocks, which is a natural result if short length LDPC code is used. Our preliminary results show that the proposed receiver is very robust to the statistics “mismatch”.

REFERENCES