Mitigating Smart Jammers in MU-MIMO via Joint Channel Estimation and Data Detection

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Abstract—Wireless systems must be resilient to jamming attacks. Existing mitigation methods require knowledge of the jammer’s transmit characteristics. However, this knowledge may be difficult to acquire, especially for smart jammers that attack only specific instants during transmission in order to evade mitigation. We propose a novel method that mitigates attacks by smart jammers on massive multi-user multiple-input multiple-output (MU-MIMO) basestations (BSs). Our approach builds on recent progress in joint channel estimation and data detection (JED) and exploits the fact that a jammer cannot change its subspace within a coherence interval. Our method, called MAED (short for MitigAtion, Estimation, and Detection), uses a novel problem formulation that combines jammer estimation and mitigation, channel estimation, and data detection, instead of separating these tasks. We solve the problem approximately with an efficient iterative algorithm. Our results show that MAED effectively mitigates a wide range of smart jamming attacks without having any a priori knowledge about the attack type.

I. INTRODUCTION

Jamming attacks pose a serious threat to the continuous operability of wireless communication systems [1]. Effective methods to mitigate such attacks are necessary as wireless systems become increasingly critical to modern infrastructure [2]. In the uplink of massive multi-user multiple-input multiple-output (MU-MIMO) systems, effective jammer mitigation is rendered possible by the asymmetry in the number of antennas between the basestation (BS), which has many antennas, and a mobile jamming device, which has one or few antennas. One possibility, for instance, is to project the receive signals on the subspace orthogonal to the jammer’s channel [3], [4]. But such methods require accurate knowledge of the jammer’s channel. If a jammer transmits permanently and with a static signature (often called barrage jamming), the BS can estimate the required quantities, for instance during a dedicated period in which the user equipments (UEs) do not transmit [5] or in which they transmit predefined symbols [4]. Instead of barrage jamming, however, a smart jammer might jam the system only at specific time instants. Such attacks may prevent the BS from estimating a jammer’s channel with simple methods.

A. State of the Art

Multi-antenna wireless systems have the unique potential to effectively mitigate jamming attacks, and a variety of multi-antenna methods have been proposed for the mitigation of jamming attacks in MIMO systems [3]–[11]. Common to all of them is the assumption—in one way or other—that information about the jammer’s transmit characteristics (e.g., the jammer’s channel, or the covariance matrix between the UE transmit signals and the jammed receive signals) can be estimated based on some specific subset of the receive signals. Fig. 1(a) illustrates the approach taken by these methods: The data phase is preceded by an augmented training phase in which the jammer’s transmit characteristics are estimated in addition to the channel matrix. This augmented training phase can either complement a traditional pilot phase with a period during which the UEs do not transmit in order to enable jammer estimation (e.g., [3], [5]), or it can consist of an extended pilot phase so that there exist pilot sequences which are unused by the UEs and on whose span the receive signals can be projected to estimate the jammer’s subspace (e.g., [8]–[10]). The estimated jammer characteristics are then used to perform jammer-mitigating data detection. Such an approach succeeds in the case of barrage jammers, but is unreliable for estimating the transmit characteristics of smart jammers: A smart jammer can evade estimation and thus circumvent mitigation by not transmitting in those samples, for instance because it is aware of the defense mechanism, or simply because it jams in brief bursts only. For this reason, our proposed method MAED unifies jammer estimation, channel estimation and data detection, see Fig. 1(b).

Many studies have already shown how smart jammers can disrupt wireless communication systems by targeting only specific parts of the wireless transmission [12]–[19] instead of using barrage jamming. Jammers that jam only the pilot phase have received considerable attention [12]–[19]. However, if a jammer is active during the pilot phase, then a BS that does defend itself against jamming attacks can estimate the jammer’s channel by exploiting knowledge of the UE transmit symbols, for instance with the aid of unused pilot sequences [8]–[10]. To disable such jammer-mitigating communication systems, a smart jammer might therefore refrain from jamming the pilot phase and only target the data phase, even if such jamming attacks have not received much attention so far [18], [19]. Other threat models that have

The method of [7] is to some extent an exception as it estimates the UEs’ subspace and projects the receive signals thereon. However, this method distinguishes the UEs’ from the jammer’s subspace based on the receive power, thereby presuming that the UEs and the jammer transmit with different power.
In the absence of a jammer, the maximum-likelihood problem for joint channel estimation and data detection is \[ \text{arg min}_{\hat{\mathbf{H}} \in \mathbb{C}^{B \times U}, \hat{\mathbf{S}}_D \in \mathbb{C}^{U \times D}} \| \mathbf{Y} - \hat{\mathbf{H}} \hat{\mathbf{S}}_D \|_F^2, \]

where, for brevity, we define \( \hat{\mathbf{S}} \triangleq [\hat{\mathbf{S}}_T, \hat{\mathbf{S}}_D] \) and leave the dependence on \( \mathbf{S}_D \) implicit. This objective already integrates.
we now formulate the MAED joint jammer estimation and
\[\tilde{\mathbf{p}} \triangleq \mathbf{I}_H - \mathbf{j}\mathbf{w}^T/\|\mathbf{j}\mathbf{w}\|^2;\] when plugging the true channel and data matrices into (2), and assuming that the contribution of the noise \(\mathbf{N}\) is negligible.

Consider now the projection onto the orthogonal subspace (POS) for jammer mitigation [3]: POS nulls a jammer by orthogonally projecting the receive signals onto the orthogonal complement of \(\text{span}(\mathbf{j})\) using the matrix \(\mathbf{P}(\mathbf{j}) \triangleq \mathbf{I}_H - \mathbf{j}\mathbf{w}^T/\|\mathbf{j}\mathbf{w}\|^2\):
\[\mathbf{P}(\mathbf{j})\mathbf{y} = \mathbf{P}(\mathbf{j})\mathbf{Hs} + \mathbf{P}(\mathbf{j})\mathbf{jw}^T + \mathbf{P}(\mathbf{j})\mathbf{N}\]
\[= \mathbf{P}(\mathbf{j})\mathbf{Hs} + \mathbf{P}(\mathbf{j})\mathbf{jw}^T + \mathbf{P}(\mathbf{j})\mathbf{N} \quad \text{(4)}\]
\[= \mathbf{P}(\mathbf{j})\mathbf{Hs} \quad \text{(5)}\]

One can then define \(\mathbf{Y}_{\mathbf{p}(\mathbf{j})} \triangleq \mathbf{Y} - \mathbf{H}\tilde{\mathbf{S}}\), and perform channel estimation and data detection using the resulting jammer-free system. The difficulty is, of course, that the projection matrix \(\mathbf{P}(\mathbf{j})\) depends on the (unknown) direction \(\mathbf{j}/\|\mathbf{j}\|\) of the jammer’s channel.

Now, consider what happens when we take the matrix \(\mathbf{P} \triangleq \mathbf{I} - \mathbf{p}\mathbf{p}^H\), \(\mathbf{p} \in \mathbb{C}^{N \times 1}\) which orthogonally projects a signal onto the orthogonal complement of some arbitrary one-dimensional subspace \(\text{span}(\mathbf{p})\), and then apply that projection to the objective of (2) as follows:
\[\|\mathbf{P}(\mathbf{Y} - \mathbf{H}\tilde{\mathbf{S}})\|_F^2.\] (6)
If we now plug the true channel and data matrices into (6) and assume that the noise \(\mathbf{N}\) is negligible, then we obtain
\[\|\mathbf{P}(\mathbf{Y} - \mathbf{H}\tilde{\mathbf{S}})\|_F^2 = \|\mathbf{P}\mathbf{j}\mathbf{w}^T + \mathbf{P}\mathbf{N}\|_F^2；\] (7)
\[\approx \|\mathbf{P}\mathbf{j}\mathbf{w}^T\|_F^2 \quad \text{(8)}\]
\[\geq 0, \quad \text{(9)}\]
with equality if and only if \(\mathbf{p}\) is collinear with \(\mathbf{j}\). In other words, the unit vector \(\mathbf{p}\) which—in combination with the true channel and data matrices—minimizes (6) is collinear with the jammer’s channel, and hence \(\mathbf{P}\) is the POS matrix.

So, assuming the noise \(\mathbf{N}\) is negligible, then \(\mathbf{p}, \mathbf{H}, \tilde{\mathbf{S}}\) minimizes (6) if (i) \(\mathbf{P}\) is the orthogonal projection onto the orthogonal complement of \(\text{span}(\mathbf{j})\), (ii) \(\mathbf{H}\) is the true channel matrix, and (iii) \(\tilde{\mathbf{S}}\) contains the true data matrix. These are, of course, exactly the goals that we wanted to attain. Following this insight, we now formulate the MAED joint jammer estimation and mitigation, channel estimation, and data detection problem:
\[{\mathbf{p}_\tau, \mathbf{H}_\tau, \mathbf{S}} = \arg \min_{\mathbf{p}_\in \mathbb{S}^N} \|\mathbf{P}\mathbf{Y} - \mathbf{H}\tilde{\mathbf{S}}\|_F^2, \quad \text{(10)}\]

Note that, compared to (6), we have absorbed the projection matrix \(\mathbf{P}\) directly into the unknown channel matrix \(\mathbf{H}\). Otherwise the columns of \(\mathbf{H}_\tau\) would be ill-defined with respect to the length of their components in the direction of \(\mathbf{j}\approx \mathbf{m}\), meaning that one could not distinguish between channel estimates \(\mathbf{H} + \alpha\mathbf{j}\mathbf{w}^T\) with different \(\alpha, \mathbf{w}\).

The dependence of \(\mathbf{P}\) on \(\mathbf{p}\) is left implicit here and throughout the paper.

B. Solving the MAED Optimization Problem

The objective (10) is quadratic in \(\mathbf{H}_\tau\), so we can derive the optimal value of \(\mathbf{H}_\tau\) as a function of \(\mathbf{p}_\tau\) and \(\mathbf{S}\), as
\[\mathbf{H}_\tau = \mathbf{P}\mathbf{Y}\tilde{\mathbf{S}}^\dagger, \quad \text{(11)}\]
where \(\tilde{\mathbf{S}}^\dagger = \tilde{\mathbf{S}}^H(\tilde{\mathbf{S}}\tilde{\mathbf{S}}^H)^{-1}\) is the Moore-Penrose pseudo-inverse of \(\mathbf{S}\). Substituting \(\mathbf{H}_\tau\) back into (10) yields
\[{\mathbf{p}_\tau, \mathbf{S}_\tau} = \arg \min_{\mathbf{p}_\in \mathbb{S}^N} \|\mathbf{P}\mathbf{Y}(\mathbf{I}_K - \tilde{\mathbf{S}}^\dagger\tilde{\mathbf{S}})\|_F^2, \quad \text{(12)}\]
Solving (12) is difficult due to its combinatorial nature, so we resort to solving it approximately. First, we relax the constraint set \(\mathbf{S}\) to its convex hull \(\mathcal{C} = \text{conv}(\mathbb{S})\) as in [24]. We then solve this relaxed problem formulation approximately by alternately performing a forward-backward splitting step in \(\mathbf{S}\) and a minimization step in \(\mathbf{P}\).

C. Forward-Backward Splitting Step in \(\mathbf{S}\)

Forward-backward splitting (FBS) [28], also called proximal gradient descent, is an iterative method that solves convex optimization problems of the form
\[\arg \min_{\mathbf{s}} f(\mathbf{s}) + g(\mathbf{s}), \quad \text{(13)}\]
where \(f\) is convex and differentiable, and \(g\) is convex but not necessarily differentiable, smooth, or bounded. Starting from an initialization vector \(\tilde{\mathbf{s}}^{(0)}\), FBS solves the problem in (13) iteratively by computing
\[\tilde{\mathbf{s}}^{(t+1)} = \text{prox}_g(\tilde{\mathbf{s}}^{(t)} - \tau^{(t)}\nabla f(\tilde{\mathbf{s}}^{(t)}); \tau^{(t)}). \quad \text{(14)}\]
Here, \(\nabla f(\tilde{\mathbf{s}})\) is the gradient of \(f(\tilde{\mathbf{s}})\), \(\tau^{(t)}\) is the stepsize at iteration \(t\), and \(\text{prox}_g\) is the proximal operator of \(g\) [29]. For a suitably chosen sequence of step sizes \(\{\tau^{(t)}\}\), FBS solves convex optimization problems exactly (provided that the number of iterations is sufficiently large). FBS can also be utilized to approximately and efficiently solve non-convex problems, even though there are typically no guarantees for optimality or even convergence [28].

For the optimization problem in (12), we define \(f\) and \(g\) as
\[f(\mathbf{S}) = \|\mathbf{P}\mathbf{Y}(\mathbf{I}_K - \tilde{\mathbf{S}}^\dagger\tilde{\mathbf{S}})\|_F^2, \quad \text{(15)}\]
and
\[g(\mathbf{S}) = \begin{cases} 0 & \text{if } \tilde{\mathbf{S}}_{[1:T]} = \mathbf{S}_T \text{ and } \tilde{\mathbf{S}}_{[T+1:K]} \in \mathcal{C} \times D \vspace{0.5cm} \vspace{0.5cm} \\
\infty & \text{else.} \end{cases} \quad \text{(16)}\]
The gradient of \(f\) in \(\tilde{\mathbf{S}}\) is given by
\[\nabla f(\tilde{\mathbf{S}}) = (\tilde{\mathbf{S}}^\dagger)^H\mathbf{Y}\mathbf{P}(\mathbf{I}_K - \tilde{\mathbf{S}}^\dagger\tilde{\mathbf{S}}) \quad \text{(17)}\]
and the proximal operator for \(g\) is simply the orthogonal projection onto the constraint set, which is
\[\text{prox}_g(\tilde{\mathbf{S}})_{u,k} = \begin{cases} [\mathbf{S}_T]_{u,k} & \text{if } k \in [1 : T] \\
\text{proj}_C([\tilde{\mathbf{S}}_{u,k}]) & \text{else,} \end{cases} \quad \text{(18)}\]
where (for QPSK) \( \text{proj}_c \) acts entry-wise on \( [S]_{u,k} \) as
\[
\text{proj}_c(x) = \min \{ \max \{ x, E/2 \}, \max \{ -x, E/2 \} \} + i \min \{ \max \{ 3-x, E/2 \}, \max \{ x, E/2 \} \}.
\]

For the selection of the stepsizes \( \{ \tau(t) \} \), we use the Barzilai-Borwein method \([30]\) as detailed in \([28],[31]\).

### D. Minimization Step in \( \tilde{p} \)

After the FBS step in \( \tilde{S} \), we minimize \([12]\) with respect to the vector \( \tilde{p} \). Defining \( \tilde{E} \triangleq \tilde{Y}(I_K - \tilde{S}^* \tilde{S}) \) and performing standard algebraic manipulations yields
\[
\tilde{p} = \arg \min_{\tilde{p} \in \mathbb{C}^D} \| \tilde{p} \tilde{E} \|_F^2
= \arg \max_{\tilde{p} \in \mathbb{C}^D} \tilde{p}^H \tilde{E} \tilde{E}^H \tilde{p}.
\]

This implies that the minimizer \( \tilde{p} \) is the unit vector which maximizes the Rayleigh quotient of \( \tilde{E} \tilde{E}^H \). The solution to this problem is the eigenvector \( v_1(\tilde{E} \tilde{E}^H) \) belonging to the largest eigenvalue of \( \tilde{E} \tilde{E}^H \), normalized to unit length \([32]\, \text{Thm. 4.2.2}]\),
\[
\tilde{p} = \frac{v_1(\tilde{E} \tilde{E}^H)}{\| v_1(\tilde{E} \tilde{E}^H) \|_2}.
\]

Calculating this eigenvector for every iteration is computationally expensive, so we only do it for the very first iteration. In all subsequent iterations, we then approximate its value with a single power method step \([33]\, \text{Sec. 8.2.1}]\), i.e., we estimate
\[
\tilde{p}^{(t+1)} = \frac{\tilde{E}^{(t+1)}(\tilde{E}^{(t+1)})^H \tilde{p}^{(t)}}{\| \tilde{E}^{(t+1)}(\tilde{E}^{(t+1)})^H \tilde{p}^{(t)} \|_2},
\]

where we initialize the power method with the subspace estimate \( \tilde{p}^{(0)} \) from the previous iteration.

### E. The MAED Algorithm

We now have all the building blocks for MAED, which is summarized in Algorithm 1. Its only input is the receive matrix \( \tilde{Y} \). MAED is initialized with \( \tilde{S}^{(0)} = 0_{U \times D} \), \( \tilde{p}^{(0)} = I_B \), and \( \tau^{(0)} = \tau_0 = 0.1 \), and runs for a fixed number of \( t_{\max} \) iterations.

#### IV. Simulation Results

### A. Simulation Setup

We simulate a massive MU-MIMO system as described in Section IV-A with \( B = 128 \) BS antennas, \( U = 32 \) single-antenna UEs, and with one single-antenna jammer. The UEs transmit for \( K = 96 \) time slots. The first \( T = 32 \) time slots are used to transmit orthogonal pilots \( S_\tau \) in the form of a \( 32 \times 32 \) Hadamard matrix (scaled to symbol energy \( E_s \)). The remaining \( D = 64 \) time slots are used to transmit QPSK payload data (also with symbol energy \( E_s \)). The channels of the UEs and the jammer are modeled as i.i.d. Rayleigh fading. We define the average receive signal-to-noise ratio (SNR) as follows:
\[
\text{SNR} \triangleq \frac{E_s \| HS \|_F^2}{E_N \| N \|_F^2},
\]

### Algorithm 1 MAED

1. **input:** \( \tilde{Y} \)
2. **initialize:** \( \tilde{S}^{(0)} = [S_T, 0_{U \times D}], \tilde{p}^{(0)} = I_B, \tau^{(0)} = \tau_0 \)
3. **for** \( t = 0 \) **to** \( t_{\max} - 1 \) **do**
4. \( \nabla f(\tilde{S}^{(t)}) = (\tilde{S}^{(t)})^H \tilde{Y}^H \tilde{p}^{(t)} \tilde{Y}(I_K - \tilde{S}^{(t)})(\tilde{S}^{(t)}) \)
5. \( \tilde{S}^{(t+1)} = \text{prox}_g(\tilde{S}^{(t)} + \tau^{(t)} \nabla f(\tilde{S}^{(t)})) \) (cf. \([18]\))
6. \( \tilde{E}^{(t+1)} = \tilde{Y}(I_K - \tilde{S}^{(t+1)})(\tilde{S}^{(t+1)}) \)
7. **if** \( t = 0 \) **then**
8. \( \tilde{p}^{(t+1)} = v_1(\tilde{E}^{(t+1)}(\tilde{E}^{(t+1)})^H) / \| v_1(\tilde{E}^{(t+1)}(\tilde{E}^{(t+1)})^H) \|_2 \)
9. **else**
10. \( \tilde{p}^{(t+1)} = \tilde{E}^{(t+1)}(\tilde{E}^{(t+1)})^H \tilde{p}^{(t)} / \| \tilde{E}^{(t+1)}(\tilde{E}^{(t+1)})^H \tilde{p}^{(t)} \|_2 \)
11. **end if**
12. \( \tilde{D}^{(t+1)} = I_B - \tilde{p}^{(t+1)}(\tilde{p}^{(t+1)})^H \)
13. \( \tau^{(t+1)} = \text{Barzilai-Borwein}(\tau^{(t)}, \tilde{S}^{(t)}, \tilde{S}^{(t+1)}, \ldots, \nabla f(\tilde{S}^{(t)}), \nabla f(\tilde{S}^{(t+1)})) \)
14. **end for**
15. **output:** \( \tilde{S}^{(t_{\max})}_{T+1:K} \)

In our evaluation, we consider four different types of jammers: (J1) barrage jammers that transmit i.i.d. jamming symbols during the entire coherence interval, (J2) pilot jammers that transmit i.i.d. jamming symbols during the pilot phase but do not jam the data phase, (J3) data jammers that transmit i.i.d. jamming symbols during the data phase but do not jam the pilot phase, (J4) sparse jammers that transmit i.i.d. jamming symbols during some fraction \( \alpha \) of randomly selected bursts of unit length (i.e., one time slot), but do not jam the remaining time slots. The jamming symbols are either circularly symmetric complex Gaussian or selected uniformly at random from the QPSK constellation. Unless stated otherwise, the jamming symbols are also independent of the UE transmit symbols \( S \).

We quantify the strength of the jammer’s interference relative to the strength of the average UE, either as the ratio between total receive energy
\[
\rho_e \triangleq \frac{E_w(\| jw \|_2^2)}{\frac{1}{T} E_S(\| HS \|_F^2)},
\]

or as the ratio between receive power during those phases that the jammer is jamming
\[
\rho_p = \frac{\rho_e}{\lambda},
\]

where \( \lambda \) is the jammer’s duty cycle and equals 1, \( T / K \), \( D / K \), or \( \alpha \) for barrage, pilot, data, or sparse jammers, respectively.

### B. Performance Baselines

Unless stated otherwise, we run MAED with \( t_{\max} = 30 \) iterations and compare it with the following baseline methods: The first baseline called “LMMSE” does not mitigate the jammer in any way and separately performs least-squares channel estimation and LMMSE data detection. The second baseline called “geniePOS” represents a jammer-robust variant of LMMSE that is furnished with ground-truth knowledge of the jammer channel \( j \) and projects the receive signals \( Y \) onto
the orthogonal complement of \( \text{span}(j) \) as in \([4]\). The method then separately performs least-squares channel estimation and LMMSE data detection in this projected subspace. The third baseline called “JL-JED” serves as a performance upper bound and operates in a jammerless but otherwise equivalent scenario. JL-JED performs joint channel estimation and data detection by approximately solving \([2]\) (with \( S \) relaxed to its convex hull \( \mathcal{C} \)) using the same FBS procedure as MAED (cf. Section III-C), except that it misses the projection \( \bar{P} \).

C. Mitigation of Strong Gaussian Jammers

We first investigate the ability of MAED to mitigate strong jamming attacks. For this, we simulated Gaussian jammers with \( \rho_J = 25 \) dB of all four jamming types introduced in Section IV-A and evaluated the performance of MAED compared to the baselines of Section IV-B (Fig. 2). We point out that the performance of geniePOS and JL-JED is independent of the considered jammer: geniePOS uses the genie-provided jammer channel to null the jammer perfectly, and JL-JED operates on a jammerless system from the beginning. Unsurprisingly, the jammer-oblivious LMMSE baseline performs significantly worse than the jammer-resistant geniePOS baseline under all attack scenarios. MAED succeeds in mitigating all four jamming attacks with very high effectiveness, even outperforming the genie-assisted geniePOS method by a considerable margin.\(^4\) The efficacy of MAED is further reflected in the fact that its BER approaches the BER of the jammerless reference baseline JL-JED to within 1 dB in all considered scenarios.

D. Mitigation of Weak QPSK Jammers

We now turn to the analysis of more restrained jamming attacks in which the jammer transmits QPSK symbols with relative power \( \rho_J = 0 \) dB during its on-phase (to pass itself off as just another UE, for instance \([7]\)). For now, we still make the assumption that the jamming symbols are independent of the UE transmit matrix \( S \). (We will consider an alternative scenario in Section IV-F.) Simulation results for all four jammer types are shown in Fig. 3. The baseline performance of geniePOS and JL-JED are again independent of the jammer and mirror the curves of Fig. 2. Because of the weaker jamming attacks, the jammer-oblivious LMMSE baseline performs much closer to the jammer-resistant geniePOS baseline. MAED again mitigates all attack types successfully, outperforming geniePOS and approaching the JL-JED baseline to within 1 dB.

Comparing Fig. 3 with Fig. 2 reveals an interesting phenomenon. MAED achieves better absolute performance under

\(^4\)The potential for MAED to outperform geniePOS is a consequence of the superiority of JED over separating channel estimation from data detection.
strong jamming attacks than under weak ones, even if the difference is subtle. The reason for this behavior is the following: MAED searches for the jamming subspace by looking for a dominant dimension of the iterative residual error $\mathbf{E}^{(t)}$, see (21). If the received jamming energy is small compared to the received signal energy, then it becomes harder to distinguish the residual errors due to the jammer’s impact from those that are caused by the errors in the channel and transmit matrix estimates $\mathbf{H}_p^{(t)}$ and $\mathbf{S}^{(t)}$.

E. What if No Jammer Is Present?

This observation leads to the question of how MAED performs if no jammer is present, or—equivalently—if a jammer does not transmit for a given coherence interval. Fig. 4(a) shows simulation results for this scenario. MAED still outperforms the LMMSE baseline at low SNR, but shows an error floor at high SNR. This error floor is caused by the slower convergence of MAED with (infinitely) weak jammers. Fig. 4(b) shows the jammerless performance of MAED for different numbers $t_{\text{max}}$ of algorithm iterations. For $t_{\text{max}} = 100$ iterations, MAED essentially achieves the excellent performance that it has in combination with strong jammers. For $t_{\text{max}} = 10$ iterations, however, MAED exhibits an error floor as high as 0.2%. In contrast, in the presence of a $\rho_e = 25$ dB strong barrage Gaussian jammer, MAED requires no more than $t_{\text{max}} = 10$ iterations for optimal performance.

The slow convergence in the absence of a jammer can be explained by the fact that, in every iteration, the strongest dimension of the residual error matrix $\mathbf{E}^{(t)}$ is mistakenly attributed to a hypothesized jammer instead of to the residual errors in the channel and transmit matrix estimates $\mathbf{H}_p^{(t)}$ and $\mathbf{S}^{(t)}$. This recurring misattribution prevents fast convergence. Nonetheless, while MAED was conceived for jammer mitigation, it shows robust performance even in the absence of jamming.

F. What Happens with a Truly Smart Jammer?

Finally, we turn to a scenario in which the jammer knows the UE pilot sequences and attacks a specific UE by transmitting that UE’s pilot sequence during the pilot phase (at $\rho_e = 25$ dB higher power). The jammer does not transmit during the data phase. Fig. 5 shows simulation results for this scenario. The geniePOS baseline nulls the jammer perfectly using its ground-truth knowledge. Thus, its performance remains unaffected regardless of the jammer. In contrast, MAED exhibits an error floor as high as 1%, only marginally outperforming the LMMSE baseline. Excluding the attacked UE and evaluating the BER among the remaining 31 UEs (labeled $\mathbf{UE}_j$ in Fig. 5(a)) reveals that the decoding errors are focused entirely on the attacked UE, and that the BER among the remaining UEs appears to be unaffected by the jammer. This experiment shows that MAED cannot identify the jammer’s subspace if the jammer passes itself off as a UE by transmitting that UE’s pilot sequence. It is not clear, however, whether such a jammer could be distinguished from a legitimate UE, even in principle. One way to prevent smart jammers from utilizing such impersonation attacks would be to use encrypted pilot sequences [34].

Finally, Fig. 5(b) shows the performance of MAED (over all 32 UEs) when the jammer transmits the average of multiple pilot sequences during the pilot phase (and refrains from transmitting during the data phase). Evidently, a jammer that targets multiple UEs quickly enables MAED to locate the jammer’s subspace and mitigate the jammer effectively.

V. CONCLUSIONS

We have proposed MAED in order to mitigate smart jamming attacks on the uplink of massive MU-MIMO systems. In contrast to existing mitigation methods, MAED does not rely on jamming activity during any particular epoch for successful jammer mitigation. Instead, our method exploits the fact that the jammer’s subspace remains constant within a coherence interval. To this end, MAED uses a novel problem formulation that combines jammer estimation and mitigation, channel estimation, and data detection. The resulting optimization problem is approximately solved using an efficient iterative algorithm. Without requiring any a priori knowledge, MAED is able to effectively mitigate a wide range of jamming attacks. In particular, MAED succeeds in mitigating attack types like data jamming and sparse jamming, for which—to the best of our knowledge—no mitigation methods have existed so far.
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