DIVIDE AND CONQUER: ONE-BIT MIMO-OFDM DETECTION BY INEXACT EXPECTATION MAXIMIZATION

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ABSTRACT

Adopting one-bit analog-to-digital converters (ADCs) for massive multiple-input multiple-output (MIMO) implementations has great potential in reducing the hardware cost and power consumption. However, distortions caused by quantization raise great challenges. In MIMO orthogonal frequency-division modulation (OFDM) detection, coarse quantization renders the orthogonal separation among subcarriers inapplicable, forcing us to deal with a problem that has a very large problem size. In this paper we study the expectation-maximization (EM) approach for one-bit MIMO-OFDM detection. The idea is to iteratively decouple the MIMO-OFDM detection problem among subcarriers. Using the perspective of block coordinate descent, we describe inexact variants of the classical EM method for providing more flexible and computationally efficient designs. Simulation results are provided to illustrate the potential of the divide-and-conquer strategy enabled by EM.

Index Terms— one-bit ADCs, MIMO-OFDM, maximum-likelihood detection, expectation-minimization

1. INTRODUCTION

The use of low-resolution analog-to-digital converters (ADCs), particularly one-bit ADCs, provides a promising candidate for power-efficient and cost-reduced implementation of massive multiple-input multiple-output (MIMO) systems [1–7]. In uplink MIMO, the number of ADCs scales with the number of antennas at the base station (BS), and using high-resolution ADCs in massive MIMO means significant rise in price and power consumption. Moreover, the use of one-bit ADCs is able to significantly simplify the designs of radio-frequency (RF) chains and automatic gain control. However, one-bit quantization incurs severe distortion on the signals, which necessitates effective signal processing techniques to combat the quantization effects.

Recently, it has been shown that given a massive number of antennas at the BS, the quantization effects of one-bit ADCs can be mitigated [3, 8, 9]. One-bit massive MIMO systems have spurred immense research interest in aspects such as asymptotic system performance analyses and efficient channel estimation/data detection. For instance, the performances of linear estimators and detectors have been studied in [2, 6, 7]; maximum-likelihood (ML) data detection has been considered in [3, 9]; approximate message passing algorithms and providing insight of the relation with unquantized MIMO-OFDM. We interpret EM from a block coordinate descent (BCD) and variational viewpoint. Such viewpoint not only provides an alternative interpretation of the classical EM, it also leads to inexact EM variants for better computational efficiency. Simulation results show that our proposed inexact EM exhibits satisfactory bit-error rate performance with reasonable computational complexity.

2. SYSTEM MODEL

2.1. Unquantized MIMO-OFDM

We first review the classical scenario of unquantized MIMO-OFDM detection to provide the reader with the context or to recall the reader the basics. Consider an uplink scenario wherein a number of single-antenna base station (BS) over a frequency-selective channel. The modulation scheme is OFDM. Under some standard assumptions (such as cyclic prefix insertion at the transmitter side and guard time removal at the receiver side), the received signal over one transmission block can be described by the following formula

\[ r_n = \sum_{k=1}^{K} H_{n,k} F^H s_k + v_n, \quad n = 1, \ldots, N, \]  

where \( r_n \in \mathbb{C}^W \) is the time-domain received signal block at the \( n \)th antenna of the BS; \( W \) is the block length; \( H_{n,k} \in \mathbb{C}^{W \times W} \) is a circulant matrix whose coefficients are the time-domain impulse response of the channel from user \( k \) to the \( n \)th antenna of the BS; \( F \in \mathbb{C}^{W \times W} \) is the (unitary) \( W \)-point DFT matrix; \( s_k \in \mathbb{C}^W \) is the symbol block transmitted by user \( k \); \( v_n \) is i.i.d. circular Gaussian noise with mean zero and variance \( \sigma_v^2 \). By the eigendecomposition...
\(H_{n,k} = F^H D_{n,k} F\), where \(D_{n,k} = \text{Diag}(\hat{h}_{n,k})\) and \(\hat{h}_{n,k}\) is the DFT of the time-domain channel impulse response, we can write
\[
\mu_n = F^H (\sum_{k=1}^{K} (\hat{h}_{n,k} \odot s_k)) + v_n,
\]
where \(\odot\) denotes the Hadamard product.

The problem is to detect \(S = [s_1, \ldots, s_K]\) from \(r_1, \ldots, r_N\), given knowledge of the channel. We consider the maximum-likelihood (ML) detector, which is known to be given by
\[
\min_{S \in SW \times K} \sum_{n=1}^{N} \| r_n - F^H (\sum_{k=1}^{K} (\hat{h}_{n,k} \odot s_k)) \|^2 ,
\]  
where \(S\) denotes the symbol constellation. The ML problem (3) is a large-scale problem, having \(WK\) unknowns (note that \(W\) is large, typically from 128 to a few thousands). However, it can be decoupled into a number of \(W\) problems. By noting \(\| r_n - F^H (\sum_{k=1}^{K} (\hat{h}_{n,k} \odot s_k)) \|^2 = \| Fr_n - \sum_{k=1}^{K} (\hat{h}_{n,k} \odot s_k) \|^2\), we can equivalently rewrite the objective function of (3) as
\[
\sum_{w=1}^{W} \| \hat{r}_w - H_w s_w \|^2 ,
\]
where \(\hat{r}_w = (\hat{r}_{1,w}, \ldots, \hat{r}_{N,w})\), with \(\hat{r}_n = Fr_n\), describes the received signal at subcarrier \(w\); \(H_w = [\hat{h}_{n,k}|_{w,s} \in C^{N \times K}\) is the MIMO channel frequency response at subcarrier \(w\); \(s_w = (s_{1,w}, \ldots, s_{K,w})\) is the multiuser symbol vector at subcarrier \(w\). Hence, we can decouple the ML problem (3) into
\[
\min_{s_k \in S^K} \| \hat{r}_w - H_w s_w \|^2 , \; \; w = 1, \ldots, W ,
\]  
which can be handled independently and have a much smaller size.

2.2. Quantized MIMO-OFDM

Now, consider the same scenario as above, but with one-bit quantized measurements
\[
y_n = Q(r_n) ,
\]  
where \(Q\) applies the in-phase quadrature-phase (IQ) quantization \(Q(x) = \text{sgn}(\text{Re}(x)) + j \cdot \text{sgn}(\text{Im}(x))\) in the element-wise fashion. The ML detector in this case is given by
\[
\min_{S \in SW \times K} F(S) := \sum_{w=1}^{W} f_{0,w}(S) ,
\]
where
\[
f_{0,w}(S) = -\log \left( \frac{\text{Re}(y_{n,w}) \text{Re}(z_{n,w})}{\sigma} \right) - \log \left( \frac{\text{Im}(y_{n,w}) \text{Im}(z_{n,w})}{\sigma} \right) ,
\]
with \(z_n = F^H (\sum_{k=1}^{K} (\hat{h}_{n,k} \odot s_k))\),
\[
\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{x}^{\infty} e^{-t^2/2} dt , \; \; \text{and} \; \; \sigma^2 = \frac{\sigma_0^2}{2} .
\]
One will find that the decoupling trick we saw in the preceding subsection does not apply to the one-bit ML problem (6). Or, to describe in an intuitive way, one-bit quantization destroys the orthogonality of OFDM. As a result, the large problem size of the ML problem (6) serves as the main challenge.

We notice only a few works that deal with the one-bit MIMO-OFDM detection problem (6) or its multi-bit quantized counterpart. In [15], the authors consider a convex relaxation of (6). They implement the convex relaxation by the projected gradient algorithm. Given the large problem scale, computing the gradient takes a non-negligible amount of computations. We can exploit the problem structure related to DFT (or FFT) to reduce the computational cost, but still the cost is not cheap. In [14], the authors consider an approximation of (6) that can be seen as unconstrained relaxation. There they apply expectation maximization (EM)—in which the M-step allows us to use the decoupling trick in unquantized MIMO-OFDM.

Curiously, the EM method for iteratively decoupling the one-bit MIMO-OFDM detection problem does not seem to have caught much attention. In this paper we aim to exploit this possibility.

3. EM FOR ONE-BIT MIMO-OFDM DETECTION

In the current study we focus on the box relaxation of the ML problem (6) under the quadrature-amplitude modulation (QAM) constellation. However, note that the idea may be expanded to some other (possibly better) detection methods—which will be future work. Let
\[
S = \{ s_R + js_I | s_R, s_I \in \{ \pm 1, \pm 3, \ldots, \pm (2D - 1) \} \}
\]
be the QAM constellation. The box relaxation of problem (6) is
\[
\min_S F(S) , \; \; \text{s.t.} \; S \in U^{W \times K} ,
\]
where \(U = \{ s_R + js_I | s_R, s_I \in [-2D + 1, 2D - 1] \}\). Our interest lies in using EM to solve problem (7), and we do it by a variational formulation. Consider the following fact.

Fact 1 Consider the signal model
\[
y = Q(r) , \; \; r = z + v , \; \; v \sim N(0, \sigma^2) .
\]
Let \(D_p\) be the class of all distributions with support \(C_p\), where \(C_1 = \mathbb{R}_+\) and \(C_{-1} = \mathbb{R}_-\). We have
\[
-\log p(y|z) = -\log \left( \frac{y^2}{2 \sigma} \right) = \min_{q \in D_0} g(z, q) ,
\]
where
\[
g(z, q) := \frac{1}{2\sigma^2} \left( E_{r \sim q}[r] - z \right)^2 + h(q) ,
\]
with \(h(q) := \frac{1}{2\sigma^2} \text{var}_r \sim q[r] + \log(\sqrt{2\pi} \sigma) + E_{r \sim q}[\log q(r)]\). The optimal solution \(q^*\) to the problem in (8) is a truncated Gaussian distribution
\[
q^*(r) = \begin{cases} \mathcal{N}(r; z, \sigma^2) & \text{if } r \notin \mathcal{A} ; \\ \mathcal{U}_{\mathcal{A}}(r) = \begin{cases} 0 , & \text{if } x \notin \mathcal{A} ; \\ 1 , & \text{if } x \in \mathcal{A} \end{cases} \end{cases}
\]
Also, the mean of the truncated Gaussian distribution is given by
\[
E_{r \sim q^*}[r] = z + y \frac{1}{\sqrt{2\pi}} e^{-z^2/(2\sigma^2)} \Phi(\frac{y}{\sigma}) .
\]

Fact 1 is a consequence of Jensen’s inequality. The proof can be found in [14] (the style of presentation there is different, but the result is the same), and it is omitted here. By applying the variational characterization (8) to \(f_{0,w}(S)\) in (6), we can recast the problem (7) as
\[
\min_{S \in U^{W \times K}} \min_{q_{n,w}} G(S, \{ q_{n,w} \}) := \sum_{n=1}^{N} \sum_{w=1}^{W} g_{n,w}(z_{n,w}, q_{n,w}) ,
\]
where \(q_{n,w} = [q_{n,w}^R, q_{n,w}^I] ; q_{n,w}^R \in D_{\text{Re}}(y_{n,w}) , q_{n,w}^I \in D_{\text{Im}}(y_{n,w}) ;
\]
with \(g_{n,w}\) given by (9). Problem (11) shows a structure suitable for the application of block coordinate descent (BCD), which we will explore in the subsequent subsections.
3.1. Exact BCD: EM Algorithm

Let us start with the classical exact BCD:

\[
q_{n+1}^{j+1} = \arg\min_{q_n,w} G(S^j, \{q_n,w\}), \quad \forall n, w, \tag{12a}
\]

\[
S^{j+1} = \arg\min_{S \in \mathcal{N}^K} G(S, \{q_{n+1}^{j+1}\}). \tag{12b}
\]

The above exact BCD scheme is an instance of the classical EM:

\[
\text{(12a) is the E-step in EM, while (12b) the M-step.}
\]

Let us study the solutions to (12a)–(12b). By Fact 1, the E-step (12a) admits a closed form

\[
(r_n^{(j+1)})_{n,w} = N(r; \Re(z_{n,w}^{(j+1)})), \quad \forall n, w,
\]

\[
(q_n^{(j+1)})_{n,w} = N(r; \Im(z_{n,w}^{(j+1)})), \quad \forall n, w,
\]

for all \(n, w\), where \(z_{n,w}^{(j+1)} = R^H(\sum_{k=1}^{K}(h_{n,k} \circ s_k^j))\). To describe the M-step (12b), let \(s_{n,w}^{(j)}\) whose real part is

\[
\Re(s_{n,w}^{(j)}) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(r_n^{(j+1)} - \Re(y_{n,w}^{(j)})^2)}{\sigma^2}}
\]

and whose imaginary part \(\Im(s_{n,w}^{(j)})\) is constructed by the same way as above, with \(\Re\) and \(\Re\) replaced by \(\Im\) and \(\Im\), respectively.

Let note, from (9),

\[
g_{n,w}(z_{n,w}, q_{n,w}^{(j+1)}) = \frac{1}{2\sigma^2} |r_n^{(j+1)} - z_{n,w}|^2 + h_{n,w}(q_{n,w}^{(j+1)}),
\]

\[
h_{n,w}(q_{n,w}) = h(q_{n,w}^R) + h(q_{n,w}^I).
\]

By applying the decoupling trick in unquantized MIMO-OFDM in (3)-(5), the M-step problem in (12b) can be rewritten as

\[
\tilde{s}_w^{j+1} = \arg\min_{s \in \mathcal{I}^K} \|R_{n}^{j+1} - H_w s_w^{j+1}\|^2, \quad w = 1, \ldots, W, \tag{14}
\]

where we decouple the problem among subcarriers. Each problem in (14) is an instance of the box-constrained quadratic program, which can be solved by algorithms such as the projected gradient (PG) algorithm and ADMM [16].

To summarize, the EM iteration (12) allows us to decouple the one-bit MIMO-OFDM detection problem into subcarrier-wise independent MIMO detection problems that take the same form as classical MIMO detection.

Remark 1 Let us discuss the computational complexity of the EM algorithm (12). In the E-step (12a), calculating \(r_{n,w}^{(j+1)}\’s requires \(2WN\) times of the calculation of function \(\Phi\). In the M-step (12b), if we use PG to solve each problem (14), the per-iteration complexity is \(O(NK)\); note that this process can be parallelized. The conversions from E-step to M-step, and from M-step to E-step, require DFT and IDFT, respectively, which demands \(O(NW \log_2 W)\) if FFT (IFFT) algorithm is used. It is desirable that the number of conversions, or the number of EM iterations, is small. There is a balance to strike between the accuracy of M-step and the computational burden of EM: exact M-step consumes a large amount of computations in solving (14), but it may help reduce the number of EM iterations. Note that we want to keep the number of EM iterations small as each EM iteration requires us to evaluate the E-step and DFT/IDFT conversion.

On the other hand, a not so accurate execution of the M-step saves computations in the M-step, but it may increase the number of EM iterations, and subsequently, the number of times that DFT/IDFT and \(\Phi\) are called. We should mention that the EM algorithm based on unconstrained relaxation in [14] results in a closed-form update for M-step; however, its performance is inferior to the box relaxation studied in this paper, as simulation results will show.

3.2. Inexact BCD: One-Step PG in M-Step

Consider an inexact variant of the BCD in (12) where we inex-actly solve the problem (14) by a one-step PG method, starting from the previous iterate \(\tilde{s}_w^j\). Specifically, the E-step (12a) remains unchanged, and the M-step (12b) is changed to

\[
\tilde{s}_w^{j+1} = \Pi_{\mathcal{I}^K}(\tilde{s}_w^j - 1/L_w(H_w^H H_w \tilde{s}_w^j - H_w^H R_{n}^{j+1})) \tag{15}
\]

for \(w = 1, \ldots, W\), where \(\Pi_{\mathcal{I}^K}(x)\) denotes the projection of a vector \(x \in \mathbb{C}^K\) onto \(\mathcal{I}^K\), and it equals

\[
\tilde{x} = \Pi_{\mathcal{I}^K}(x)
\]

\[
\Leftrightarrow \tilde{x}_k = \mathrm{Re}(x_k)_{2D^2 - 2D^2 + 1} + j\mathrm{Im}(x_k), k = 1, \ldots, K,
\]

with \([a]_b = \min\{\max\{a, b\}\}, L_w = 2\sigma_{\max}(H_w)^2\) with \(\sigma_{\max}(H_w)\) being the largest singular value of \(H_w\). One may be curious about the convergence of such inexact EM scheme. The answer is yes, and the idea is to see the above inexact EM scheme as an instance of majorization-minimization [17]; we omit the details owing to space limitation.

It is interesting to note that this one-step PG inexact EM scheme looks similar (but is not identical) to IBOX [15], where a PG algorithm is directly applied to solve problem (7). Particularly, they have the same order of per-iteration complexity of evaluating the \(\Phi\) function, DFT/IDFT conversion and matrix-vector products. Our empirical experience suggests that both the one-step PG EM (12a) and (15) and IBOX suffer from slow convergence in terms of the numbers of EM iterations, and they incur a large amount of computations for evaluating DFT/IDFT.

3.3. Inexact BCD: Inexact Update in M-Step

This subsection presents an alternative scheme that may provide a better balance between the accuracy of M-step and the number of EM iterations. We apply FISTA-type accelerated projected gradient (APG) to problem (14) with limited number of iterations \(B\) (e.g. 5~10 iterations) [18]. Let \(\tilde{x} = \tilde{s}_w^j\) be the input of the APG solver, where we omit the subscript \(w\) for notational simplicity. Starting from \(\tilde{x}\), the APG solver in each iteration \(i, i = 0, \ldots, B - 1\), reads as

\[
x^{i+1} = \Pi_{\mathcal{I}^K}(w^i - 1/L(H_w^H H_w w^i - H_w^H R_{n}^{j+1})), \tag{16}
\]

where \(w^i = x^i + \alpha_i(x^i - x^{i-1})\) with \(\alpha_i = \frac{\xi_i - 1}{\xi_i}, \xi_i = \frac{1}{\sqrt{1 + 4\xi_{i-1}}}, \xi_1 = 1\) and \(x^m = x^0 \Leftarrow \tilde{x}\). Then, we set \(s^{i+1} = x^0\) as the output. The APG method has a theoretical faster convergence rate than the PG method. As of the writing of this paper, we are unable to definitively confirm whether the above inexact BCD scheme guarantees convergence to an optimal solution. Some related studies in optimization, such as [19, 20], provide strong indication that the answer should be yes. However, the optimization variables \(h_{n,w}\) are distributions, not vectors. This gives us new challenge. Convergence analysis will be our future work.

We summarize the above three EM algorithms in Algorithm 1.
Algorithm 1 EM for One-Bit MIMO-OFDM Detection
1: given an initialization $S_0$, iteration number $j = 0$. 
2: repeat
3: $z_{n}^{j+1} = E^H(\sum_{k=1}^{K}(h_{n,k} \otimes s_k^j))$
4: E-step: 
5: $Re(r_{n,w}^{j+1}) = Re(r_{n,w}^{j+1}) + Re(y_{n,w})\frac{e^{-\|r_{n,w}^{j+1}\|^2/(2\sigma^2)}}{\sqrt{2\pi}\sigma}$ 
6: $Im(r_{n,w}^{j+1}) = Im(r_{n,w}^{j+1}) + Im(y_{n,w})\frac{e^{-\|r_{n,w}^{j+1}\|^2/(2\sigma^2)}}{\sqrt{2\pi}\sigma}$ 
7: $\tilde{r}_{n,w}^{j+1} = Fr_{n,w}^{j+1} \cdot \tilde{r}_{n,w}^{j} = (\tilde{r}_{n,w}^{j+1} + \tilde{r}_{n,w}^{j})_{N,K}$ 
8: M-step: 
9: update $S^{j+1}$ by one of the three strategies in Sections 3.1- 3.3 
10: $j = j + 1$
11: until some stopping criterion is satisfied.

4. SIMULATION RESULTS

In this section, we demonstrate the performance of the EM algorithms by numerical simulations. We consider the inexact EM, or BCD, scheme in Section 3.3, with $B = 5$ APG steps for each EM iteration. The benchmarked algorithms are the zero-forcing (ZF) detectors over each subcarrier and under full-resolution and one-bit ADCs, the 1BOX algorithm [15] and the unconstrained regularized EM algorithm [14]. For 1BOX, we decrease the stepsize from $\sqrt{2}/64$ to 1/512 and increase the iteration number from 3 to 200 for better performance [15]. We terminate our EM algorithm if the difference of two successive iterates satisfies $\|S^{j+1} - S^j\|_F \leq 2 \times 10^{-4} \|S^0\|_F$ or if the maximum iteration number 200 is reached.

We adopt a widely-used multipath channel model for millimeter-wave massive MIMO with uniform linear array at the BS [21]. The time-domain channel from user $k$ to all the antennas of the BS at the $l$th tap is generated by

$$h_{l,k} = \sum_{l=1}^{\infty} \beta_{l,k} a_{l,k}^l, \quad l = 1, \ldots, L, \quad k = 1, \ldots, K,$$

where $L$ is the number of channel taps; $\beta_{l,k} \sim \frac{1}{\sqrt{L}}CN(0,1)$ is the complex channel gain; $a_{l,k}^l$ is the steering vector

$$a_{l,k}^l = \begin{bmatrix} 1, e^{-j\frac{\pi}{\lambda}d \sin(\theta_{1,k})}, \ldots, e^{-j\frac{\pi}{\lambda}d \sin(\theta_{L-1,k})} \end{bmatrix}^T,$$

with $d$, $\lambda$ and $\theta_{l,k}$ being the inter-antenna spacing, carrier wavelength and path angle, respectively; $\eta$ is the number of paths. Throughout the simulation, we set $L = 16$, $\frac{\lambda}{d} = \frac{1}{2}$, $\eta = 4$ and randomly generate the path angles $\theta_{l,k}$’s from $[0, \pi]$. The number of users and the number of OFDM subcarriers are $(N, K, W) = (256, 36, 512)$ in Fig. 1(a) and $(N, K, W) = (256, 20, 512)$ in Fig. 1(b). We see that the EM algorithms and 1BOX achieve better performance than the one-bit ZF detector. Also, it is seen that the proposed EM algorithm performs better than the unconstrained regularized EM in [14]; the performance gain at the mid-to-high SNR region is about 5 dB. In Fig. 2, we increase the problem dimension to $(N, K, W) = (512, 36, 1024)$ and test the algorithms under 16-ary QAM. We were unsuccessful in obtaining reasonable results with 1BOX. Encouragingly, it is seen that the EM algorithms can still yield satisfactory BER performance. Again, the proposed EM algorithm shows better BER performance than the EM in [14].

In Fig. 3, we show the convergence of EM algorithms in Section 3, namely, 1) EM by exact BCD, 2) EM with one-step PG in the M-step, 3) EM with $B = 5$ APG steps in the M-step, by showing the negative log-likelihood value $f(S)$ in problem (6) versus the iteration number in a random trial. The setting is the same as those in Fig. 2 with SNR = 5 dB. We see that the negative log-likelihood monotonically decreases with respect to EM iterations for all the EM algorithms. Also, the inexact FISTA-type EM achieves almost the same convergence rate as the exact EM, which converges in 20 ~ 40 EM iterations.

5. CONCLUSION

In this paper, we studied exact and inexact EM schemes for one-bit ML MIMO-OFDM detection. We demonstrated the efficiency of handling one-bit MIMO-OFDM detection by the divide-and-conquer strategy enabled by EM. Future work will study how this divide-and-conquer strategy can be expanded to other MIMO detection methods, particularly those that have powerful detection performance in classical MIMO detection.
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