

#### MPDQ-Based High-Order QAM Detection Scheme for Massive MIMO with Low-Precision Quantization

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# **Background of 5G**

\* Key requirement: 1000 folds of increase in data traffic

#### Three main directions



## **Massive MIMO**

#### What is massive MIMO and why ?

- Use hundreds of antennas at the BS to simultaneously serve a set of users
- Increase the spectral and energy efficiency by orders of magnitude



F. Rusek, D. Persson, B. K. Lau, E. G. Larsson, T. L. Marzetta and O. Edfors, "Scaling up MIMO: Opportunities and challenges with very large arrays," *IEEE Signal Processing Magazine*, vol.30, pp.40-60, 2013.

# Challenges





# **Motivation**





- → suffers from the matrix inversion

What is more, all of them dealing with high-order QAM need 12-16 bits to achieve acceptable performance

**MMSE** is suboptimal







## **System Model**

•  $Q(\cdot)$  is the quantization operation

Y=Q(HX+N)

 $\diamond$  *b*-bit uniform quantizer. **Q**(•) is defined as

$$r = \mathbf{Q}(c) = \begin{cases} sign(c) \cdot \left( \left[ \frac{c}{\Delta} \right] \Delta + \frac{\Delta}{2} \right) , & |c| < G + \frac{\Delta}{2} \\ sign(c) \cdot G , & |c| \ge G + \frac{\Delta}{2} \\ \frac{\Delta}{2} , & c = 0 \end{cases}$$

where  $\Delta = \max(\mathbf{C})/2^{b-1}$  is quantization step, and  $G=([|\max(\mathbf{C})|/\Delta])$  is saturation level.

the upper and lower quantitative bounds for further detection:

$$B_{up}(r) = \begin{cases} +\infty, & \text{if } r = G \\ r + \frac{\Delta}{2}, & \text{otherwise} \\ B_{low}(r) = \begin{cases} -\infty, & \text{if } r = -G \\ r - \frac{\Delta}{2} & \text{otherwise} \end{cases}$$

## **Estimation method**

The approximate marginal distribution is calculated as

$$\widehat{p}_{x_j|Y}^t(x_j|Y) \propto p_x(x_j) \prod_{i=1}^{2N_r} m_{z_i \to x_j}^t(x_j).$$

Finally, the estimate  $\widehat{X}$  is computed as

$$\widehat{x}_j^t = \int x \widehat{p}_{x_j|Y}^t(x_j|Y) dx$$

In message passing algorithm, the messages are calculated as

$$m_{y_i \leftarrow x_j}^t(x_j) \propto p_x \prod_{l \neq j} m_{y_l \to x_j}^t(x_j)$$
,

 $m_{y_i o x_j}^t(x_j) \propto \int p_{y|hx} \prod_{k \neq j} m_{y_i \leftarrow x_k}^{t-1}(x_j) dx_{\setminus j}$  ,

#### The factor-graph representation

 Here , approximated message passing algorithm is exploited to iteratively estimate the unknown vector.



- In Massive MIMO systems, the messages sent between the transceiver nodes are assumed to approximately Gaussian distributed.
- Therefore can be calculated by their first and second order of statistical properties, i.e. the expectation and the variance.

## **MPDQ-hl algorithm**

- But in traditional message passing algorithm, the observation vector Y is obtained directly.
- In our scheme, Y is observed after b bit quantization, so we proposed a method to estimate the vector Z before the quantization, the expression are as follows:

$$\begin{split} \widehat{p}_{i}^{t} &= \sum_{j} h_{ij} \widehat{x}_{i}^{t} - v p_{i}^{t} \widehat{y}_{i}^{t-1} , \\ v p_{i}^{t} &= \sum_{j} h_{ij}^{2} v x_{i}^{t-1} \\ \widehat{z}_{i}^{t} &= \frac{1}{v p_{i}^{t} + \sigma^{2}} (\mathsf{E}[u_{i} | u_{i} \in q^{-1}(y_{i})] - \widehat{p}_{i}^{t}) , \\ v z_{i}^{t} &= \frac{1}{v p_{i}^{t} + \sigma^{2}} (1 - \frac{\operatorname{Var}[u_{i} | u_{i} \in q^{-1}(y_{i})]}{v p_{i}^{t} + \sigma^{2}}) , \end{split}$$

where the expectation and the variance are evaluated with respect to  $u_i \sim N(\hat{p}_i^t, vp_i^t + \sigma^2).$  $q^{-1}(y_i) = [B_{low}(y_i), B_{up}(y_i)].$ 

## **MPDQ-hl algorithm**

• Given the prior information  $p_{\chi}$ , the received measurement signal Y, the channel state information H, the noise variance  $\sigma^2$ , and the mapping q of the quantizer Q(•), the estimation of X is shown below.

$$\hat{r}_{j}^{t} = \hat{x}_{j}^{t-1} + vr_{j}^{t} \sum_{i} h_{ij} \hat{z}_{i}^{t},$$
$$vr_{j}^{t} = \left[\sum_{i} h_{ij}^{2} v z_{i}^{t}\right]^{-1},$$
$$\hat{x}_{j}^{t} = \mathbf{E}[\mathbf{x} | \hat{r}_{j}^{t}, vr_{j}^{t}],$$
$$vx_{i}^{t} = \mathbf{Var}[\mathbf{x} | \hat{r}_{i}^{t}, vr_{i}^{t}],$$

where the expectation and the variance are evaluated with respect to  $p(\mathbf{x} | \hat{r}_{j}^{t}, vr_{j}^{t}) \propto N(\mathbf{x}; \hat{r}_{j}^{t}, vr_{j}^{t})p_{\chi}(\bullet).$ 

## **Complexity Analysis**

- The MPDQ-hl algorithm is perfect dealing with non-linear system, so is suitable for quantization problem, we exploit it for lowprecision problem.
- The proposed algorithm reduces the complexity with just matrix multiplication.
- The complexity of the proposed scheme is proved to be one order of magnitude smaller than that of conventional MMSE.
- Its rapid convergence property is analyzed by MSE.



#### Simulation parameters:

- 256-QAM is utilized in the system.
- The data size L is 300.
- $\diamond$  the iterative termination parameter *tol* is set as  $10^{-3}$ .
- The number of trials for each Monte Carlo simulation is 1000 times.
- The proposed algorithm is compared with quantized MMSE (qMMSE) and unquantized MMSE.



Fig. 1. 7 bits quantization with different MIMO configurations  $M \times N$ 



Fig. 2. 128 $\times$ 256 MIMO with different quantization bits



Fig. 3. MSE at each iteration with different MIMO parameters



# Conclusion

- In this paper, we have proposed the MPDQ-hl algorithm to detect high-order QAM signals for massive MIMO systems with lowprecision quantization.
- In 256-QAM systems, simulation results show that MPDQ-hI with 7 bits quantization could achieve better BER performance than MMSE with full precision system, <u>thus saving 3 bits or more by</u> <u>comparison</u>.
- Compared with the conventional MMSE algorithm with the complexity of O(N<sup>3</sup>), the complexity of MPDQ-hl can be reduced to O(N<sup>2</sup>), where N is the number of transmitting antennas.
- Its rapid convergence property is analyzed by MSE.
- It can reduce the power consumption in Massive MIMO systems.

# Thank You !