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Angular domain precoding-based PAPR reduction for massive MIMO systems

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Dear editor,

Massive multiple-input multiple-output (MIMO) is a key technology of the fifth generation wireless communication systems [1, 2]. Angle division multiple access (ADMA) [3] is one of the multiple access technologies to explore the spatial degrees of freedom. It is based on the channel characteristic of each user in the angle domain, thereby the dimension of channel matrix is reduced due to the sparse distribution of users [4].

ADMA-based massive MIMO systems are regarded as multi-angle systems, and this property can be learned from that of the multi-carrier systems, like the systems of orthogonal frequency division multiplexing (OFDM). In multi-angle systems, the high peak-to-average power ratio (PAPR) of the transmit signals also brings big challenges to the radio frequency (RF) components. Fortunately, the PAPR reduction methods in multi-angle systems can be inspired by that in multi-carrier systems [5]. There are many different PAPR reduction techniques for OFDM systems, such as clipping, precoding, tone reservation, and so on [6]. However, these studies always need the tradeoff between the PAPR reduction and the bit error rate (BER), signal power, or computational complexity.

In this study, a novel precoding-based PAPR reduction technique is proposed, i.e., the signal recovery with PAPR reduction (SRPR) algorithm. This scheme was inspired by the alternating direction method of multipliers (ADMM) algorithm and the finite-set precoding solutions [7]. It takes full advantages of resources in the angle domain to perform PAPR reduction in ADMA-based massive MIMO systems. Numerical results demonstrate that the enhanced PAPR reduction is achieved almost without BER performance loss.

System model. Consider the ADMA-based massive MIMO downlink transmission scheme, where the number of BS antennas is M. There are K randomly distributed single-antenna users served by the base station (BS). We suppose that the angular channel index of all users and the channel state information (CSI) for the downlink are known at the BS. Given the angular channel index B_k^{ro}, the angular rotation parameter ϕ_k^{ro}, channel estimation $\hat{\boldsymbol{g}}_k^{\mathrm{T}}$, and the corresponding estimation of CSI in the angular domain $\tilde{\boldsymbol{g}}_k^{\mathrm{T}}$, $k = 1, \ldots, K$. All users are divided into G groups after user scheduling in the downlink transmission. Let the g-th group user index set as U_g, $g = 1, \ldots, G$, and the number of this group is $K_g = |U_g|$. Suppose a narrow band and flat fading channel environment, and the received signal is given by

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{x} + \boldsymbol{n}, \tag{1}$$

where $\boldsymbol{y} \in \mathbb{C}^{K_g}$, $\boldsymbol{H} \in \mathbb{C}^{K_g \times M}$ is the downlink channel matrix between the BS and the g-th group users, and we assume that the downlink channel gain of each path is independent complex Gaussian random variable with zero mean and unit variance. $\boldsymbol{x} \in \mathbb{C}^M$ is the transmit signal vector at the BS, and noise vector $\boldsymbol{n} \in \mathbb{C}^{K_g}$. The relationship

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between the downlink channel estimation and the corresponding estimation in the angular domain is expressed as

$$\hat{\boldsymbol{g}}_k = \boldsymbol{\Phi}(\phi_k)^{\mathrm{H}} \boldsymbol{F}^{\mathrm{H}} \tilde{\boldsymbol{g}}_k, \tag{2}$$

where $\hat{\boldsymbol{g}}_k \in \mathbb{C}^M$, the angular domain rotation matrix is $\boldsymbol{\Phi}(\phi_k) = \mathrm{diag}([1, \mathrm{e}^{\mathrm{j}\phi_k}, \ldots, \mathrm{e}^{\mathrm{j}(M-1)\phi_k}])$ with $\phi_k \in [-\pi/M, \pi/M]$, and $\boldsymbol{F}$ is the discrete Fourier transform (DFT) matrix.

PAPR reduction in the angular domain. Let $\boldsymbol{s} \in \mathbb{C}^{K_g}$ denote the symbol vector intended for users at the current group, and $\boldsymbol{s}$ can be mapped into M-dimensional $\boldsymbol{x}$ after the PAPR-reduction-based multi-user precoding in the angular domain,

$$\boldsymbol{x} = \mathcal{P}\left(\boldsymbol{s}, \tilde{\boldsymbol{H}}, \tilde{\boldsymbol{F}}_M^{\mathrm{H}}\right), \tag{3}$$

where $\tilde{\boldsymbol{H}} = [\tilde{\boldsymbol{g}}_1^{\mathrm{T}}, \tilde{\boldsymbol{g}}_2^{\mathrm{T}}, \ldots, \tilde{\boldsymbol{g}}_{K_g}^{\mathrm{T}}]^{\mathrm{T}}$ is the channel estimation in the angular domain, and $\tilde{\boldsymbol{F}}_M^{\mathrm{H}} \in \mathbb{C}^{M \times M}$ is the inverse DFT (IDFT)-like matrix:

$$\tilde{\boldsymbol{F}}_M^{\mathrm{H}} = \left[\tilde{\boldsymbol{f}}_0^*, \tilde{\boldsymbol{f}}_1^*, \ldots, \tilde{\boldsymbol{f}}_{M-1}^*\right], \tag{4}$$

where $\tilde{\boldsymbol{f}}_i^* = \boldsymbol{\Phi}(\tilde{\phi}_l)^{\mathrm{H}} \boldsymbol{f}_i^*$ with $\boldsymbol{f}_i$ being the i-th column of DFT matrix, $i = 0, 1, \ldots, M-1$. And $\tilde{\phi}_l$ is the rotation parameter of the l-th column of IDFT matrix, yields

$$\tilde{\phi}_l = \begin{cases} \phi_k, & \text{if } l \in B_k^{\mathrm{ro}}, k \in U_g, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

The transmit signal $\boldsymbol{x}$ should satisfy $\boldsymbol{s} = \boldsymbol{H}\boldsymbol{x}$ with perfect CSI, and the received signal is given by

$$\boldsymbol{y} = \boldsymbol{s} + \boldsymbol{n}. \tag{6}$$

Because $K_g < M$, then an appropriate solution of $\boldsymbol{x}$ with low PAPR can be obtained by applying optimization method:

$$\min_{\boldsymbol{x}, \mu} \quad \|\boldsymbol{s} - \mu \boldsymbol{H}\boldsymbol{x}\|_2^2 + \mu^2 K_g \sigma^2 \quad \text{s.t.} \quad \boldsymbol{x} \in \mathcal{X}^M,\ \mu > 0, \tag{7}$$

where μ is the precoding factor, $\boldsymbol{x}$ is restricted in a finite set $\mathcal{X}^M$, and σ^2 is the noise variance.

The SRPR algorithm is summarized in Algorithm 1, which can be used for the low-resolution quantized or finite-set precoding-based PAPR reduction and make a minimum mean square error (MMSE) estimation of $\boldsymbol{x}$,

$$\hat{\boldsymbol{x}} = \boldsymbol{x}^t + \boldsymbol{\Omega}\left(\boldsymbol{s} - \bar{\boldsymbol{H}}\boldsymbol{x}^t\right), \tag{8}$$

where $\boldsymbol{\Omega} = (\bar{\boldsymbol{H}}^{\mathrm{H}}\bar{\boldsymbol{H}} + \gamma^t \mathbf{I})^{-1}\bar{\boldsymbol{H}}^{\mathrm{H}}$, with γ^t being the Lagrangian augmented factor at iteration t. In order to obtain the unbiased estimation, $\boldsymbol{\Omega}$ is replaced by $\boldsymbol{D}\boldsymbol{\Omega}$ with a diagonal matrix $\boldsymbol{D} = [\mathrm{diag}(\boldsymbol{\Omega}\bar{\boldsymbol{H}})]^{-1}$. $\prod_{\mathcal{X}^M}(\cdot)$ is the mapping function, and α is the damping factor. Then, the optimization of μ is obtained by the derivation of (7).

We observe that the computational complexity of matrix inversion of $\boldsymbol{\Omega}$ in Algorithm 1 is very high, especially for the massive MIMO systems. Because the penalty factor is usually very large, we have $\boldsymbol{\Omega} \approx \frac{1}{\gamma^t}\bar{\boldsymbol{H}}^{\mathrm{H}}$. Consequently, a concise SRPR (CSRPR) algorithm is shown in Algorithm 2. Additionally, the computational complexity can be further reduced when $\mu = \sqrt{\mathrm{tr}((\boldsymbol{H}\boldsymbol{H}^{\mathrm{H}})^{-1})/MP}$ with the transmit power P at each antenna. Therefore, the computational complexity of Algorithm 2 with fixed μ is $\mathcal{O}(T(2MK+M) + 2MK + 2M)$, and for the case with changing μ, it needs additional $\mathcal{O}(2MK + 2K)$ multiplications at each update.

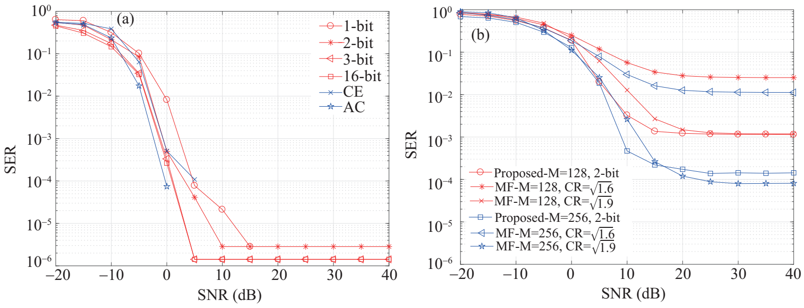
Algorithm 1 SRPR

Require: $\boldsymbol{s}, \boldsymbol{H}, T_1, T_2$,
$t = 0, \boldsymbol{x}^0 = \mathbf{0}, \gamma^0 = 1, \mu^0 = 1, \alpha = 0.95$;
Ensure: $\boldsymbol{x} = \boldsymbol{x}^{t+1}$;
while $t \leqslant T_1$ **do**
$\bar{\boldsymbol{H}} = \mu^t \boldsymbol{H}$;
$\boldsymbol{\Omega} = (\bar{\boldsymbol{H}}^{\mathrm{H}}\bar{\boldsymbol{H}} + \gamma^t \mathbf{I})^{-1}\bar{\boldsymbol{H}}^{\mathrm{H}}$;
$\boldsymbol{D} = [\mathrm{diag}(\boldsymbol{\Omega}\bar{\boldsymbol{H}})]^{-1}$;
$\boldsymbol{x}^{t+1} = \prod_{\mathcal{X}^M}(\boldsymbol{x}^t + \boldsymbol{D}\boldsymbol{\Omega}(\boldsymbol{s} - \bar{\boldsymbol{H}}\boldsymbol{x}^t))$;
$\gamma^{t+1} = \mathrm{tr}(\bar{\boldsymbol{H}}^{\mathrm{H}}\bar{\boldsymbol{H}})/\|\boldsymbol{s} - \bar{\boldsymbol{H}}\boldsymbol{x}^{t+1}\|_2^2$;
if $\bmod(T_2, t+1) == 0$ **then**
$\mu^{t+1} = \frac{\mathrm{Re}(\boldsymbol{s}^{\mathrm{H}}\boldsymbol{H}\boldsymbol{x}^{t+1})}{\|\boldsymbol{H}\boldsymbol{x}^{t+1}\|_2^2 + K_g\sigma^2}$;
else
$\mu^{t+1} = \mu^t$;
end if
$\boldsymbol{x}^{t+1} \leftarrow \alpha \boldsymbol{x}^t + (1-\alpha)\boldsymbol{x}^{t+1}$;
$\gamma^{t+1} \leftarrow \alpha \gamma^t + (1-\alpha)\gamma^{t+1}$;
$t \leftarrow t+1$;
end while

Algorithm 2 CSRPR

Require: $\boldsymbol{s}, \boldsymbol{H}, T_1, T_2$,
$t = 0, \boldsymbol{x}^0 = \mathbf{0}, \mu^0 = 1, \alpha = 0.95$;
Ensure: $\boldsymbol{x} = \boldsymbol{x}^{t+1}$;
while $t \leqslant T_1$ **do**
$\bar{\boldsymbol{H}} = \mu^t \boldsymbol{H}$;
$\boldsymbol{\Theta} = \left[\mathrm{diag}\left(\bar{\boldsymbol{H}}^{\mathrm{H}}\bar{\boldsymbol{H}}\right)\right]^{-1}\bar{\boldsymbol{H}}^{\mathrm{H}}$;
$\boldsymbol{x}^{t+1} = \prod_{\mathcal{X}^M}(\boldsymbol{x}^t + \boldsymbol{\Theta}(\boldsymbol{s} - \bar{\boldsymbol{H}}\boldsymbol{x}^t))$;
if $\bmod(T_2, t+1) == 0$ **then**
$\mu^{t+1} = \frac{\mathrm{Re}(\boldsymbol{s}^{\mathrm{H}}\boldsymbol{H}\boldsymbol{x}^{t+1})}{\|\boldsymbol{H}\boldsymbol{x}^{t+1}\|_2^2 + K_g\sigma^2}$;
else
$\mu^{t+1} = \mu^t$;
end if
$\boldsymbol{x}^{t+1} \leftarrow \alpha \boldsymbol{x}^t + (1-\alpha)\boldsymbol{x}^{t+1}$;
$t \leftarrow t+1$;
end while

Numerical results and discussions. Three precoding methods are adopted, i.e., multi-user con-



Parameter	Value
BS antennas	128, 256
BS antenna architecture	ULA
BS antenna interval	$\lambda/2$
User number	32
Antenna number per user	1
Beam number per user	11
User protection interval	2
Scattering path	100
Angular spread	2°
Constellation modulation	4-QAM, 16-QAM

(c)

Figure 1 (Color online) (a) SER of 4-QAM for different precoding PAPR reduction when $M=128$; (b) SER of 16-QAM with different number of BS antennas; (c) simulation parameters.

stant envelope (CE), annulus constrained (AC), and low-resolution quantized precoding. Then the joint precoding technique and PAPR reduction are achieved by using the proposed algorithm. Notably, the 1-bit quantized precoding can be considered as the special case of the CE precoding. Simulation parameters are shown in Figure 1(c).

It is observed in Figure 1(a) that the low SER performance can be achieved with low-resolution quantized precoding, and the performance gap of symbol error rate (SER) between 3-bit and 16-bit precoding are almost negligible. Furthermore, the SER performance of CE, AC and quantized precoding schemes is comparable for a large range of SNR. However, the SER performance of AC precoding and 3-bit or higher-resolution quantized precoding schemes is obtained at the cost of PAPR reduction, whereas the CE, 1-bit and 2-bit quantization precoding techniques achieve a good trade-off between SER and PAPR reduction. It is not shown here due to the limited space.

Figure 1(b) investigates the SER of 16-QAM with the proposed technique and matched filtering (MF) precoding clipping method, while the BS is equipped with 128 antennas or 256 antennas. The clipping ratio (CR) in Figure 1(b) is defined as the square root ratio between the clipping power and the signal average power. The SERs of both schemes improve a lot with the increase of the number of BS antennas. The performance gap of MF and proposed technique is reduced when CR increases from $\sqrt{1.6}$ to $\sqrt{1.9}$ in the regime of high SNR. However, the PAPR of MF is about 2.7875 dB when $M=256$ and CR=$\sqrt{1.9}$, whereas the PAPR of the proposed method is less than 1 dB when $M=256$.

Conclusion. In this study, a massive MIMO-ADMA system is established, and a precoding-based optimization problem is introduced for PAPR reduction and signal recovery. The SRPR and CSRPR algorithms are developed as the precoding schemes of PAPR reduction for massive MIMO-ADMA system. Furthermore, the proposed technique with low-resolution quantized precoding is efficient and hardware-friendly, which is very important in practice. Numerical results demonstrate the outstanding PAPR reduction and SER performance when compared with other schemes.

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