Receiver-Based Bayesian PAPR Reduction in OFDM

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High PAPR in OFDM Signals

- Though OFDM signals are used in many wireless communication standards they suffer from high PAPR.
- The high PAPR causes either of the following
  - Nonlinear distortions from the high power amplifier (HPA).
  - Inefficient use of HPA due to power backoff in order to avoid distortions.

Existing Schemes for PAPR Reduction

- There are numerous existing transmitter based schemes including
  - Selected mapping (SLM)
  - Partial transmit sequence (PTS)
  - Tone reservation (TR)
- These schemes are computationally expensive
- Cause reduction in battery lifetime

Contributions

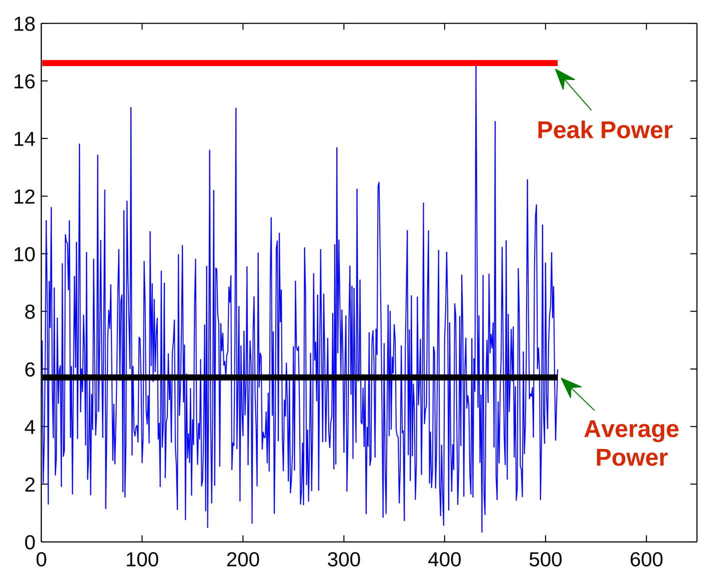
- The proposed scheme is
  - Bayesian and uses the *apriori* knowledge of the signal statistics.
  - weighted to focus on most probable clipped locations.
  - phase augmented to acknowledge the anti-phase nature of clipping signal.
  - able to refine the initial estimates of the signal statistics if exact estimates are not available.

Clipping at the Transmitter

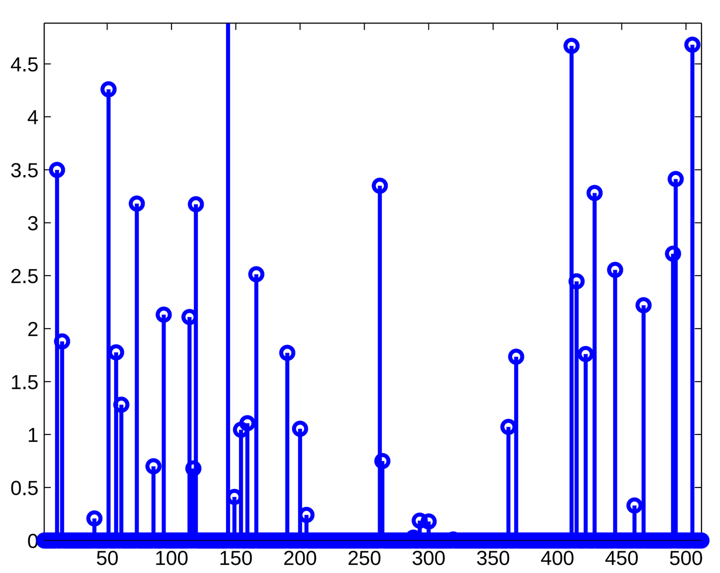
- A clipping signal $\mathbf{c}$ is added to the the time domain high PAPR signal $\mathbf{x}$ to get the clipped signal $\mathbf{x}_p$

$$x_p(i) = \begin{cases} \gamma e^{j\theta_{x(i)}} & \text{if } |x(i)| > \gamma \\ x(i) & \text{otherwise} \end{cases}$$

- The amplitude of the clipped signal $\mathbf{x}_p$ is limited to clipping threshold γ.
- The clipping signal $\mathbf{c}$ is sparse in time domain.

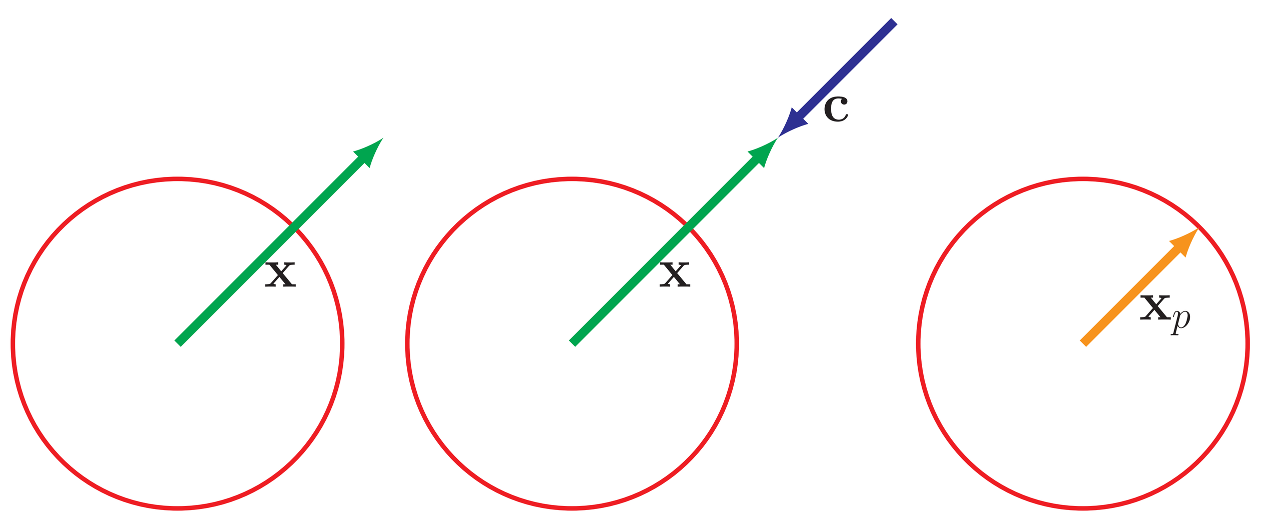


(a) High PAPR OFDM Signal



(b) Sparse Clipping Signal $\mathbf{c}$

- The clipping signal $\mathbf{c}$ only changes the magnitude of the signal $\mathbf{x}$ and not the phase ($\mathbf{c}$ is anti-phased with $\mathbf{x}$).



- With intention of recovering the clipping signal at the receiver, $K \ll N$ carriers are reserved for sparse signal recovery.
- These few subcarriers are enough to estimate the sparse vector $\mathbf{c}$ [1].

Reconstruction at the Receiver

- Only the magnitude of the unknown signal $\mathbf{c}$ is to be found.
- Consider a set of equations

$$\mathcal{Y}'_m = \mathbf{\Phi}_m \mathbf{c} + \mathcal{Z}'_m$$

where $\mathcal{Y}'_m \in \mathbb{C}^M, \mathbf{\Phi}_m \in \mathbb{C}^{M\times N}$ and $\mathcal{Z}'_m \in \mathbb{C}^M$.
- The phase of complex $\mathbf{c}$ is merged into $\mathbf{\Phi}_m$, making the unknown $\mathbf{c} \in \mathbb{R}^N$ (and hence the term phase augmented).
- Hence the above system can be split as

$$\begin{bmatrix} \mathrm{Re}\{\mathcal{Y}'_m\} \\ \mathrm{Im}\{\mathcal{Y}'_m\} \end{bmatrix} = \begin{bmatrix} \mathrm{Re}\{\mathbf{\Phi}'_m\} \\ \mathrm{Im}\{\mathbf{\Phi}'_m\} \end{bmatrix} \mathbf{c} + \begin{bmatrix} \mathrm{Re}\{\mathcal{Z}'_m\} \\ \mathrm{Im}\{\mathcal{Z}'_m\} \end{bmatrix}$$

$$\bar{\mathcal{Y}} = \bar{\mathbf{\Phi}}\mathbf{c} + \bar{\mathcal{Z}}$$

- The system of equation given above is solved using a CS scheme for clipping recovery.

Weighted Reconstruction

- For sparse signal reconstruction, most probable locations of active elements are found.
- Initially each location has a success probability ρ.
- The signals elements close to γ have higher probability of being active.
- We use $\mathbf{w} = \gamma - |\hat{\mathbf{x}}_p|$ as a weighting vector
- Assign higher probabilities to locations where $w(i)$ is small

$$p(\mathcal{S}) = \prod_i^N p_i, \text{ for all } i = 1, 2, \cdots, N$$

where $p_i = \rho e^{-w(i)}$.

Proposed Reconstruction Scheme

1) **estimate** $\hat{\mathbf{x}}_\mathbf{p} = \mathbf{F}^\mathsf{H}\mathbf{\Lambda}^{-1}\mathbf{F}\mathbf{y}$
2) $\hat{\gamma} = \max(\hat{\mathbf{x}}_\mathbf{p})$.
3) $\hat{\sigma}_n^2 = \mathrm{var}(\bar{\mathcal{Y}})$.
4) $\mathbf{w} = \hat{\gamma} - |\hat{\mathbf{x}}_\mathbf{p}|$.
5) $\hat{\rho}_o = \mathrm{Q}\left(\frac{\hat{\gamma}-\mu}{\sigma}\right)$, an initial estimate, where μ and σ are the mean and standard deviation of $\hat{\mathbf{x}}_p$, respectively.
6) $i = 0$, **repeat**
7) $p_k = \hat{\rho}_i e^{-w(k)}$, $k = 1, 2, \ldots, N$.
8) **Compute** $\hat{\mathbf{c}}_{\text{ammse}}$ and $\hat{\rho}_{i+1}$ using the technique discussed in [2]
9) **until** $\left(\frac{|\hat{\rho}_i - \hat{\rho}_{i-1}|}{\hat{\rho}_{i-1}} < 0.02\right)$
10) $\hat{\mathbf{c}} = \mathbf{\Theta}_\mathbf{c}|\hat{\mathbf{c}}_{\text{ammse}}|$
11) $\hat{\mathbf{x}} = \hat{\mathbf{x}}_\mathbf{p} - \hat{\mathbf{c}}$

Results

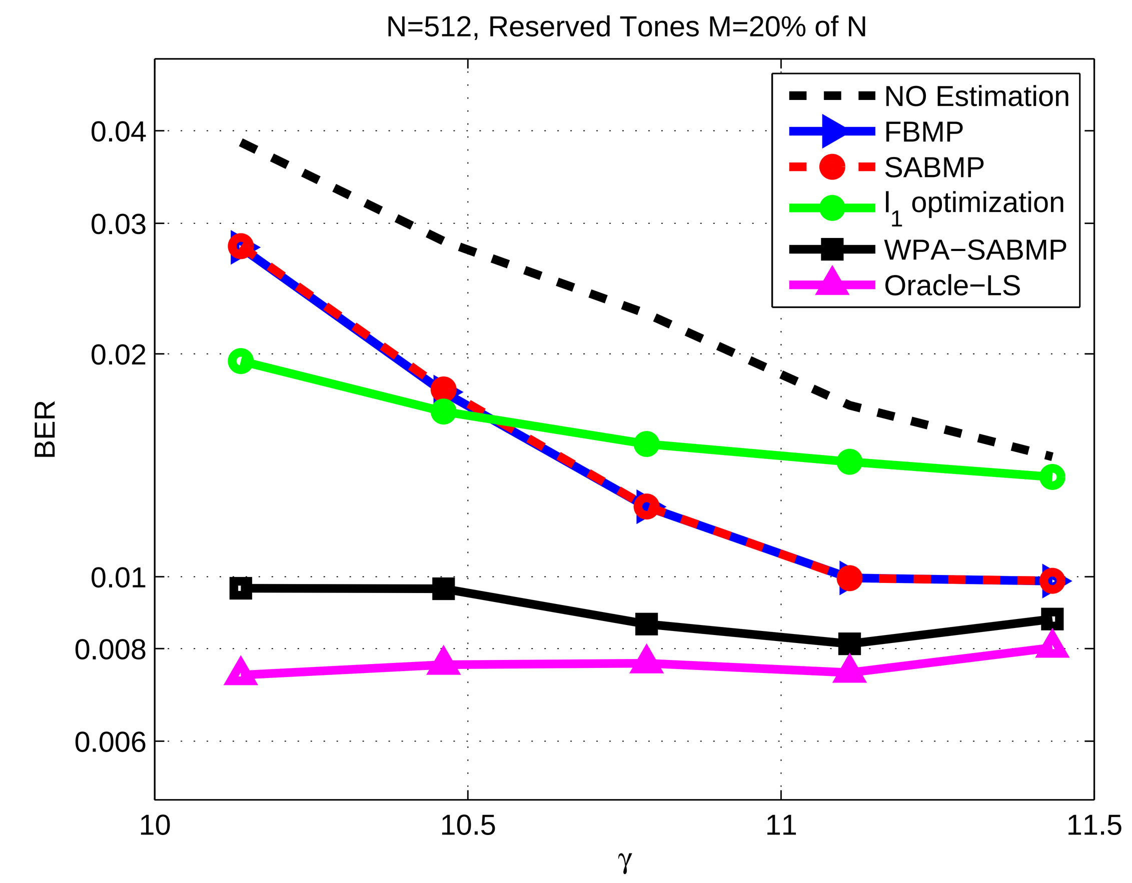


Figure: BER versus γ using exact parameter values

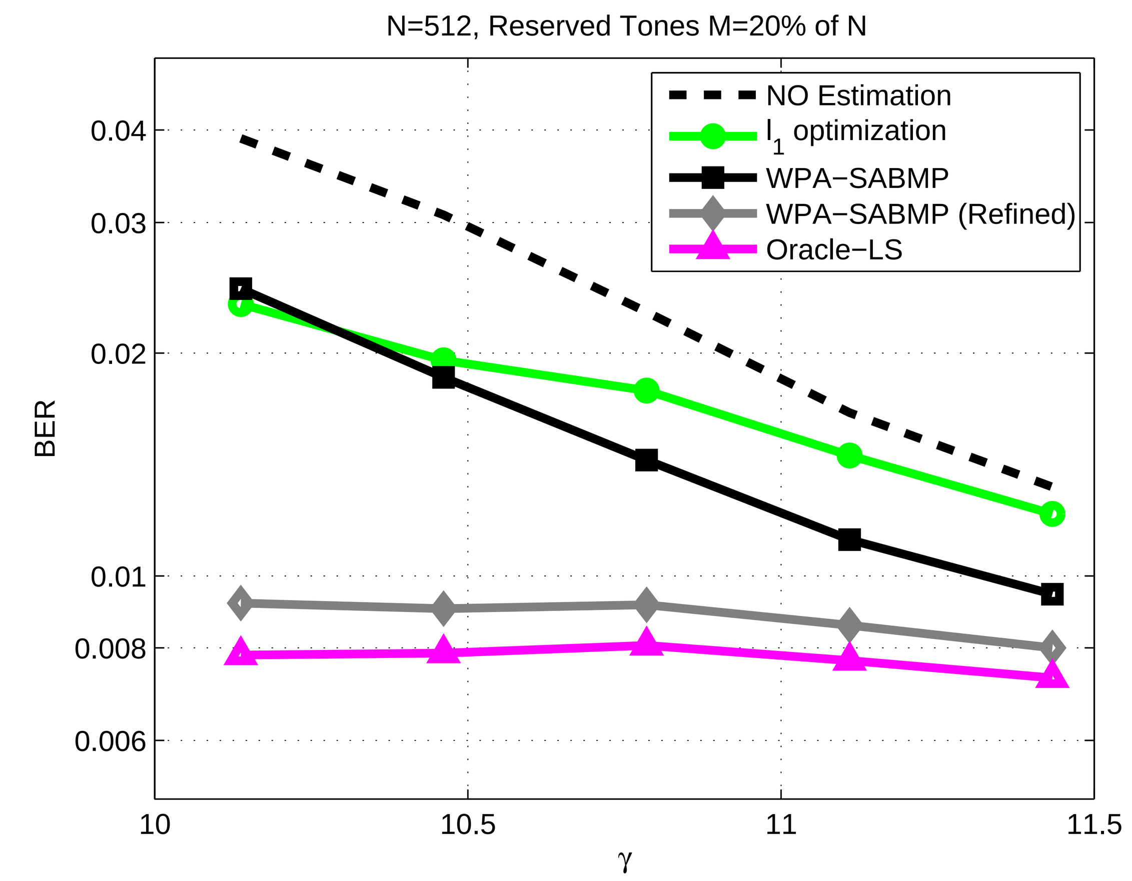


Figure: BER versus γ using rough estimates of the parameters

References

[1] E. Candes and J. Romberg, "Sparsity and incoherence in compressive sampling," *Inverse problems*, vol. 23, no. 3, p. 969, 2007.

[2] M. Masood and T. Y. Al-Naffouri, "Sparse Reconstruction using Distribution Agnostic Bayesian Matching Pursuit," *IEEE Trans. Signal Process.*

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