Improved High-Order Modulation Maximal Likelihood System

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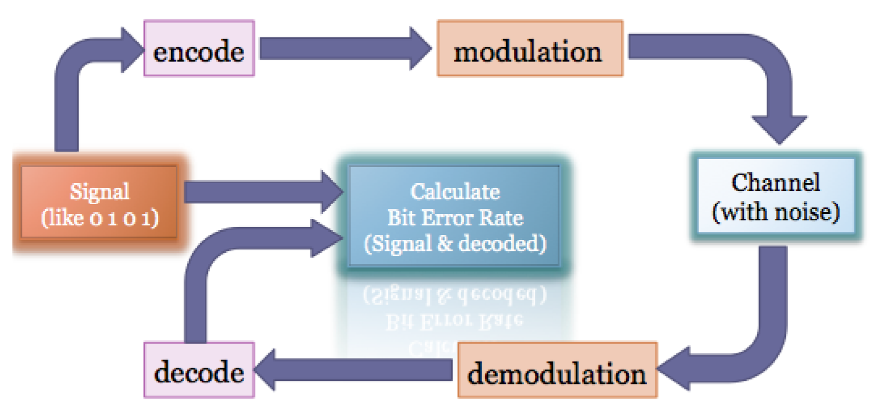
1. Introduction



- Modulation
  - We will use 16 QAM
- Channels and Flat Fading
- Multiple Input Multiple Output (MIMO)
- Bit Error Rate (BER)
  - The BER we are concerned about is 10^{-3}
- Signal to Noise Ratio (SNR)

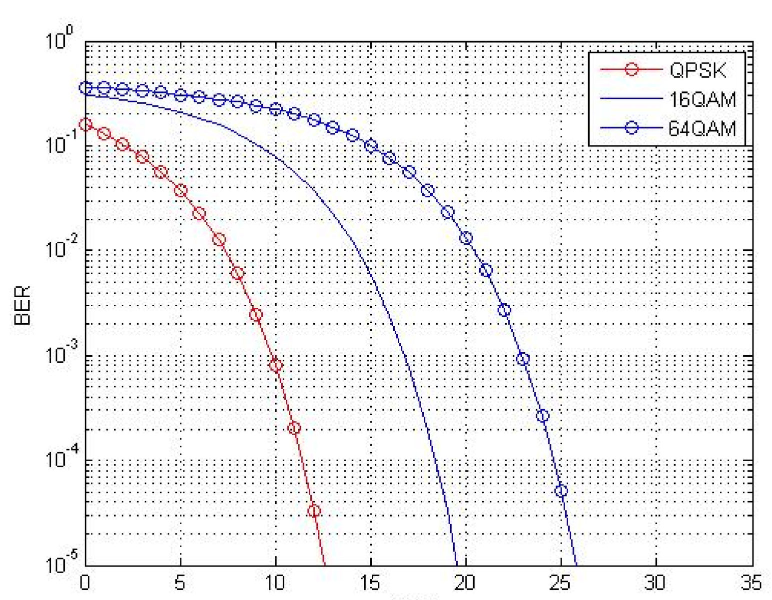


Figure 1: BER vs SNR for 4, 16 and 64 QAM

2, Equalization Methods

- Model $y = Hx + n$
- Retrieve x from y using equalization methods
- Maximum Likelihood (ML)
  - Highest performance method, but slowest
  - Finds $\hat{x}$ by minimizing over $J = |y - H\hat{x}|$ and iterating over all possible $\hat{x}$.
  - Exactly maps our guess $\hat{x}$ to one of the complex values represented in the modulation
- Minimum Mean Square Error (MMSE)
  - Fastest method, but low performance
  - Minimize over $\{E\{(Wy - x)(Wy - x)^*\}\}$ by iterating over all W
  - W is the minimum expected error, defined by $W = H^*(HH^* + \frac{1}{p}I)^{-1}$, where H^* is the Hermitian of H and p is the power of the signal.
  - Creates an estimation for the complex value from the modulation, and will not necessarily exactly map to a value from the modulation.

3. Our Equalization Methods

- Simplified ML Method I (SML)
  - SINR from MMSE discovers how many accurate bits
  - Discovers what quadrant the signal belongs to, then subquadrent, if the SINR is large enough
  - ML is used to approximate the remaining bits

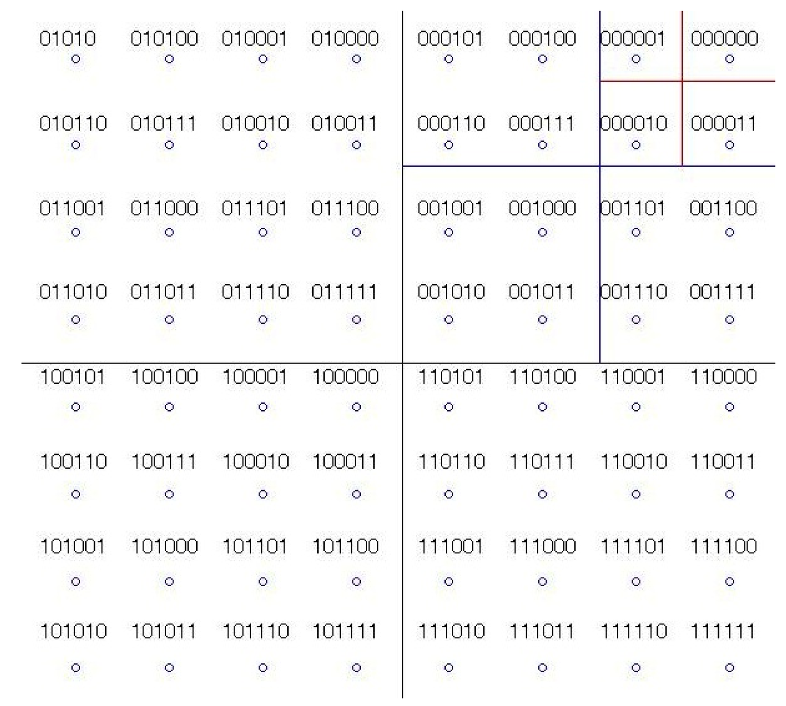


Figure 2: Bit labeling for SML

- Simplified ML Method 2 (SML2)
  - Takes initial guess from MMSE to narrow down the possibilities for bit values
  - Uses the average power for each of the QAMs to form areas that the the guesses can fall within
  - ML is used to approximate the remaining bits

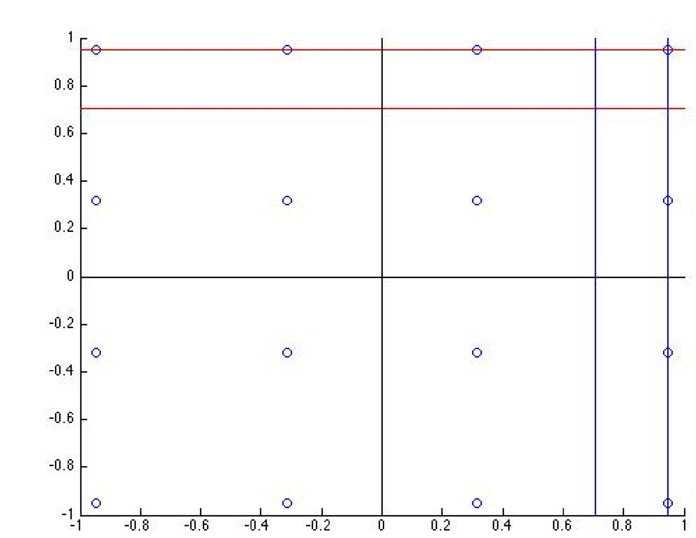


Figure 3: Narrowing down choices for SML2

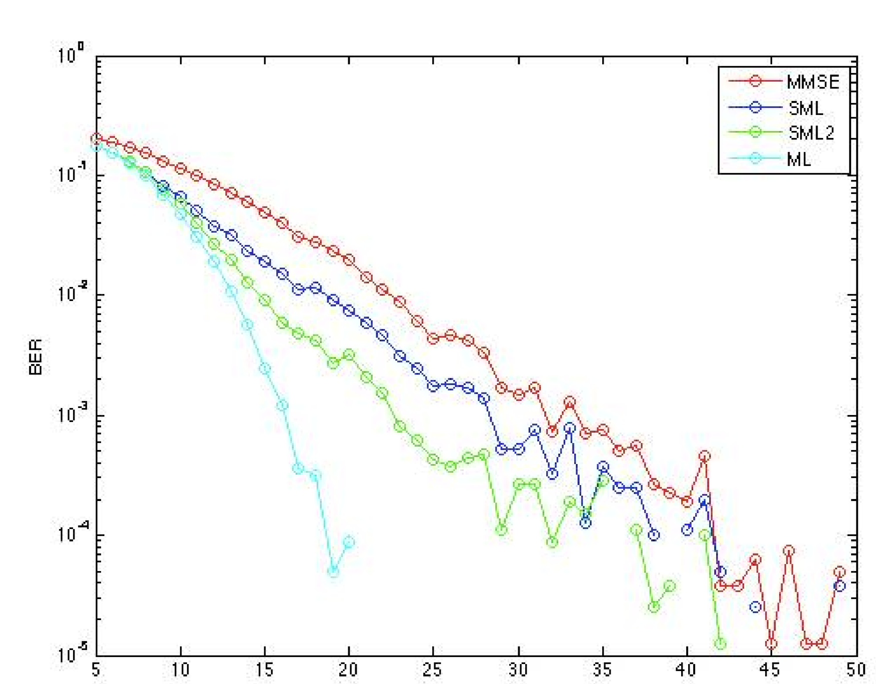


Figure 4: BER for MMSE, SML, SML 2, and ML

4. Channel Coding

- Convolutional Encoder
- Trellis Mapping
- Convolutional Decoder
- Hard Decision

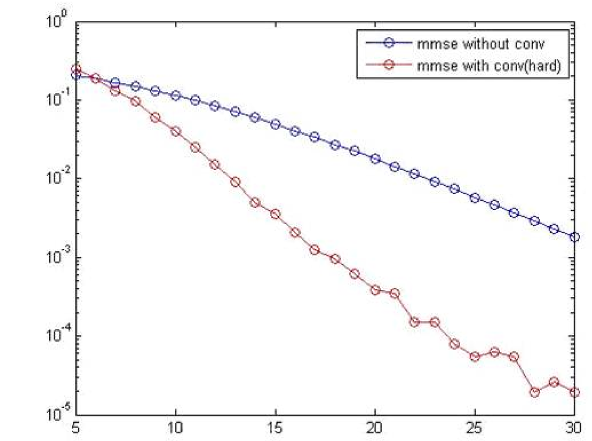


Figure 5: MMSE with Convolutional Coding, Hard Decision

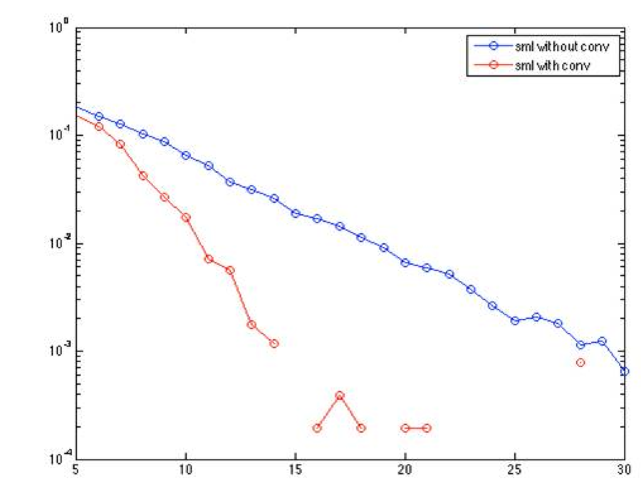


Figure 6: SML with Convolutional Coding, Hard Decision

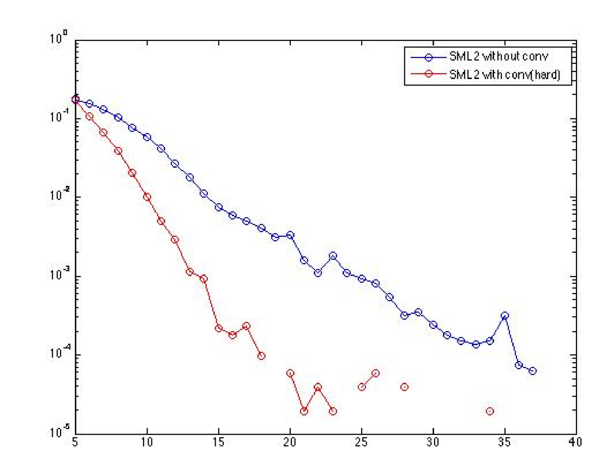


Figure 7: SML2 with Convolutional Coding, Hard Decision

- Soft Decision
- Quanitizer

Input signal to quantizer	Output of quantizer and input to decoder	Interpretation
< 0.001	0	Most confident 0
0.001 <= X < 0.1	1	Second most confident 0
0.1 <= X < 0.3	2	Third most confident 0
0.3 <= X < 0.5	3	Least confident 0
0.5 <= X < 0.7	4	Least confident 1
0.7 <= X < 0.9	5	Third most confident 1
0.9 <= X < 0.999	6	Second most confident 1
>=0.999	7	Most confident 1

Figure 8: Numbers for Soft Decision

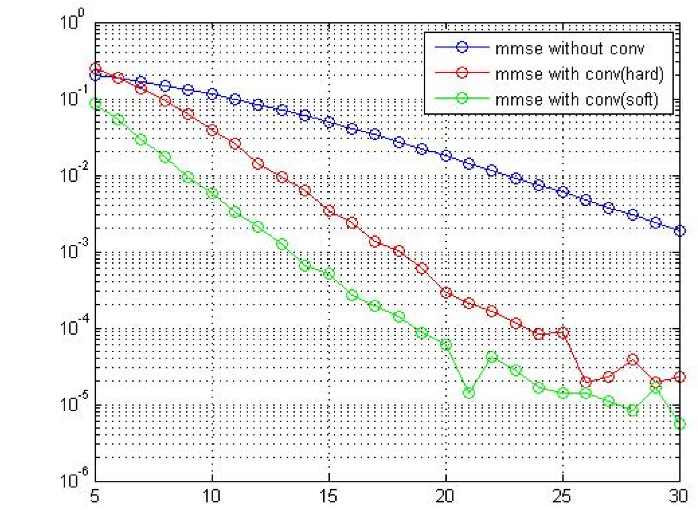


Figure 9: MMSE with Soft and Hard Decoding

5. Conclusions

Method	Time (sec/1000 trials)	Min Power for 10^{-3} BER
MMSE	0.17	35
SML 1	2	27
SML 2	99	23
ML	440	17
MMSE Hard (Conv)	2	17
SML 1 Hard (Conv)	101	14
SML 2 Hard (Conv)	437	14
MMSE Soft (Conv)	0.5	14

The time represents how many seconds it took the computer to run the various equalization methods in seconds for 1000 trials. The power is the minimum number of decibels to achieve a BER of 10^{-3} or less.

6. Further Considerations

We hope to further reduce the time complexity and increase the BER by implementing Turbo Codes. Through some initial experimentation, we expect that the SNR with decrease to about 7 or 8 dB. We hope to even further reduce the SNR by utilizing HARQ in addition to the Turbo Codes.

7. Acknowledgements

Thanks to IPAM for sponsoring our project through the UCLA-RIPS program. Thanks also to HKUST for providing their campus and resources to us this summer. Thanks also to our academic mentor, Dr. Albert Ku, and our industrial mentors from HUAWEI, Dr. Yinggang Du and Dr. Rui Wang.

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