Thesis Defense

On the Performance Analysis over Generalized and Composite Fading Channels: A Unified Approach

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August 26, 2015

Contents

Introductory Background | Fading Channels

This thesis is concerned with providing a unified approach to modeling or approximating wireless fading channels.

- Large-scale (Shadowing) Effect
  - Lognormal, Inverse-Gaussian, Gamma.

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- Large-scale (Shadowing) Effect
  - Lognormal, Inverse-Gaussian, Gamma.
- Small-scale (Multipath) Effect
  - **Conventional**: Rayleigh, Nakagami-m, Weibull-m, Rician.
  - **Generalized**: $\alpha - \mu$, $\kappa - \mu$, $\eta - \mu$.

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Introductory Background | Composite Fading Channels (1)

Performance analysis over multipath or shadowing scenarios alone is relatively tractable. However, extending the analysis to composite fading channels is rather cumbersome and intractable.

- Examples:
  - Nakagami-m/Lognormal (NL) model (no closed-form)

$$f_\gamma(x) = \frac{2\lambda m^m}{\Gamma(m)\sqrt{2\pi}\zeta} \int_0^\infty \frac{x^{m-1}}{\overline{\gamma}^m \sigma^{m+1}} e^{-\frac{mx}{\overline{\gamma}\sigma}} e^{\frac{-(10\log\sigma)^2}{2\zeta^2}} \mathrm{d}\sigma. \quad (1)$$

  - $\kappa-\mu$ Shadowed model [1] (complicated)

$$f_\gamma(\gamma) = \frac{\mu^\mu m^m (1+\kappa)^\mu}{\Gamma(\mu)\overline{\gamma}(\mu\kappa+m)^m} \left(\frac{\gamma}{\overline{\gamma}}\right)^{\mu-1} \times \exp\left(-\frac{\mu(1+\kappa)\gamma}{\overline{\gamma}}\right) {}_1\mathcal{F}_1\left(m,\mu;\frac{\mu^2\kappa(1+\kappa)}{\mu\kappa+m}\frac{\gamma}{\overline{\gamma}}\right), \quad (2)$$

[1] J. F. Paris, "Statistical Characterization of κ-μ Shadowed Fading," IEEE Trans. Veh. Technol., vol. 63, no. 2, pp. 518–526, Feb. 2014.

Introductory Background | Composite Fading Channels (2)

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  - The RIGD and G-distribution:
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- Still complex and not a general solution.

Introductory Background | Composite Fading Channels (3)

- Another alternative proposed by Atapattu et al. [2]
  - Several models were approximated using the mixture Gamma ($\mathcal{MG}$) distribution via gauss-quadrature approximations.
  - Approximates: NL, K, K_G, $\eta-\mu$, $\kappa-\mu$, Hoyt, and Nakagami-m.
- The pdf is given by

$$f_\gamma(\gamma)=\sum_{i=1}^{K}\frac{\alpha_i}{\overline{\gamma}}\frac{x}{\overline{\gamma}}^{\beta_i-1}\exp(\frac{\zeta_i x}{\overline{\gamma}})$$

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  - Pros: Very tractable, arbitrarily accurate.
  - Cons: Still not generalizable to all fading models.

[2] S. Atapattu, C. Tellambura, and H. Jiang, "A Mixture Gamma Distribution to Model the SNR of Wireless Channels," IEEE Trans. Wireless Commun., vol. 10, no. 12, pp. 4193–4203, Dec. 2011.

Objectives

We propose to approximate generalized and composite fading channels using mixture distributions, namely using the mixture of Gaussian (MoG) and mixture Gamma ($\mathcal{MG}$) distributions.

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  - Useful for finding the maximum likelihood estimator (MLE) of any distribution in the exponential family.

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- EM was coined by Dempster *et al.* [3].
  - Useful for finding the maximum likelihood estimator (MLE) of any distribution in the exponential family.
- VB is the full Bayesian variant of EM; maximize the maximum *a posteriori* (MAP) estimate.

[3] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via the EM algorithm," J. Royal Statistical Soc., vol. 39, no. 1, pp. 1–38, 1977.

The MoG distribution

- We approximate the amplitude of fading models by the MoG distribution, resulting in the following amplitude and signal-to-noise (SNR) pdfs:

The MoG distribution

$$f_\alpha(x) = \sum_{j=1}^{C} \frac{\omega_j}{\sqrt{2\pi}\eta_j} \exp(-\frac{(x-\mu_j)^2}{2\eta_j^2}), \tag{3}$$

$$f_\gamma(\gamma) = \sum_{j=1}^{C} \frac{\omega_j}{\sqrt{8\pi\bar{\gamma}}\eta_j} \frac{1}{\sqrt{\gamma}} \exp(-\frac{(\sqrt{\frac{\gamma}{\bar{\gamma}}}-\mu_j)^2}{2\eta_j^2}), \tag{4}$$

where C is the number of mixture components, and ω_j, μ_j, η_j^2 correspond to the weights, means and variances, respectively.

Expectation-Maximization

Original Problem formulation

Assume that an observed vector $\boldsymbol{y} = \{y_1, \ldots, y_N\}$, drawn from any of the fading channel amplitudes, follows the MoG distribution. Then we need to find the MLE as follows:

$$
\begin{aligned}
\theta_{MLE} &= \arg\max_{\theta \in \hat{}} \mathbb{L}_{(MoG)} (\theta | \boldsymbol{y}, C) = \arg\max_{\theta \in \hat{}} \ln\ p(\boldsymbol{y}|\theta, C), \\
&= \arg\max_{\theta \in \Theta} \sum_{i=1}^{N} \ln\Big[\sum_{j=1}^{C} \frac{\omega_j}{\sqrt{2\pi\eta_j^2}} \exp\Big(-\frac{(y_i - \mu_j)^2}{2\eta_j^2}\Big)\Big]. \qquad (5)
\end{aligned}
$$

- Maximization of (5) directly is analytically not tractable.
- Instead, the problem is re-formulated such that it fits the EM framework.

Expectation-Maximization

Problem re-formulated according to EM

Regard the observed data $\boldsymbol{y}$ as incomplete and assume that we have a discrete latent random variable called $Z \in \{1, \ldots, C\}$, such that the complete random variable is $X = (Y, Z)$.
Correspondingly, we maximize the complete-data log-likelihood function or the so-called $\mathbb{Q}$-function as follows:

$$\begin{aligned} \theta^{(t+1)} &= \arg\max_{\theta \in \Theta} \mathbb{Q}\left(\theta | \theta^{(t)}\right) \\ &= \arg\max_{\theta \in \Theta} \mathbb{E}_{X|y,\theta^{(m)}}[\log p_X(X|\theta)], \\ &= \arg\max_{\theta \in \Theta} \sum_{i=1}^{N} \sum_{j=1}^{C} \rho_{ij}^{(t)} \left(\ln \pi_j - \ln \mathcal{N}(y_i|\mu_j, \sigma_j)\right), \end{aligned} \tag{6}$$

Expectation-Maximization

EM treatment to the MoG distribution

- $\mathbb{E}$-step: Compute $\rho_{ij}^{(t)}$.
- $\mathbb{M}$-step: Compute:

$$\omega_j^{(t+1)} = \frac{1}{N}\sum_{i=1}^{N}\rho_{ij}^{(t)}, \quad \mu_j^{(t+1)} = \frac{1}{N\omega_j^{(t+1)}}\sum_{i=1}^{N}\rho_{ij}^{(t)}y_i,$$

$$\eta_j^{(t+1)} = \frac{1}{N\omega_j^{(t+1)}}\sum_{i=1}^{N}\rho_{ij}^{(t)}\left(y_i - \mu_j^{(t)}\right)^2, j = 1, .., C.$$

- This iterative procedure is terminated upon convergence, that is when

$$\mathbb{L}_{(MoG)}^{(t+1)}(\theta|\mathbf{y}, C) - \mathbb{L}_{(MoG)}^{(t)}(\theta|\mathbf{y}, C) < \delta, \tag{7}$$

Expectation-Maximization

- Pros:
  - Accurate *w.r.t.* mean-square error (MSE) and Kullback-Leibler (KL) divergence.
- Cons:
  - Still no method to determine the optimal C.
  - Singularities can occur during simulation due to overfitting.

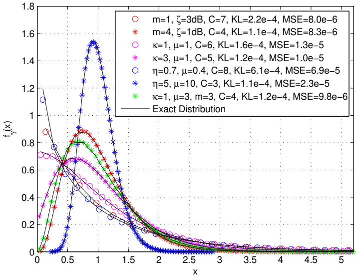

Figure: MoG approximation for different channel models.

Bayesian Information Criterion for EM

- Bayesian information criterion (BIC) is an information-theoritic method to determine an appropriate number of mixture components.
- Introduced by Gideon Schwarz in 1978 [4].
- Adds a penalty term to the negative log-likelihood as follows:

$$BIC_C = -2\mathbb{L}_{(MoG)}(\hat{\theta}|\boldsymbol{y}, C) + C \ln N$$

[4] G. Schwarz and Others, "Estimating the dimension of a model," The annals of statis- tics, vol. 6, no. 2, pp. 461–464, 1978.

Bayesian Information Criterion for EM

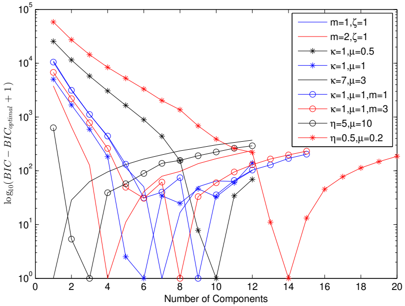

Figure: Normalized BIC versus the number of components

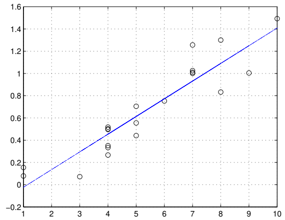

Figure: Optimal number of components versus the amount of fading

Variational Bayes (VB)

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  - Possibility of facing singularities and over-fitting.
  - No effecient method to determine the number of mixture components directly (on-the-go).
- VB aims to maximize the *a posteriori* rather than the likelihood. Moreover, the parameters to be estimated, θ, are treated as nondeterministic (random variables).

Variational Bayes

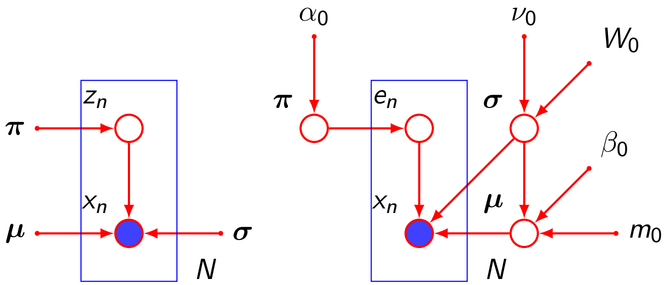

Figure: Bayesian networks representing EM (left) and VB [5] (right).

[5] C. M. Bishop, Pattern Recognition and Machine Learning (Information Science and Statistics). Secaucus, NJ, USA: Springer-Verlag New York, Inc., 2006.

Variational Bayes

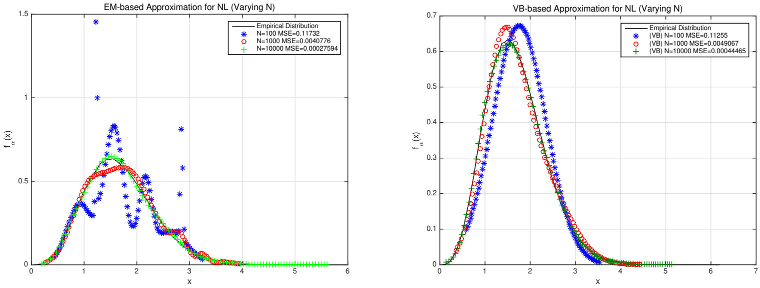

Figure: EM- (left) and VB-based (right) approximations of the NL distribution with $m = 2$. The blue, red, and green distributions correspond to 1E2, 1E3, and 1E4 data points with $C = 6$.

Performance Analysis | Intro

To provide simplifying and unifying analysis for wireless communication systems over various generalized and composite fading channel models.

- Moment generating function (MGF).
  - Average Channel Capacity, $\overline{\mathcal{C}}$.
  - Symbol Error Rate of L-branch MRC system.
- Raw Moments.
  - Amount of Fading (AoF).
- Outage Probability.

Performance Analysis | Results

$$M_{\gamma}(s) = \sum_{i=1}^{C} \frac{\omega_i}{\sqrt{\beta_i}} \exp\left(\frac{\mu_i^2 s}{\beta_i}\right) Q\left(-\frac{\mu_i}{\eta_i \sqrt{\beta_i}}\right), \quad (8)$$

$$\mathbb{E}[\gamma^n] = \sum_{i=1}^{C} \omega_i \overline{\gamma}^n \eta_i^{2n} 2^n \frac{\Gamma\left(n+\frac{1}{2}\right)}{\sqrt{\pi}} {}_1\mathcal{F}_1\left[-n, \frac{1}{2}, -\frac{\mu_i^2}{2\eta_i^2}\right], \quad (9)$$

$$\mathrm{AoF} = \frac{\mathbb{E}[\gamma^2] - \mathbb{E}[\gamma]^2}{\mathbb{E}[\gamma]^2}. \quad (10)$$

$$F(\gamma_{th}) = \sum_{i=1}^{C} \omega_i \left[Q\left(-\frac{\mu_i}{\eta_i}\right) - Q\left(\frac{\sqrt{\frac{\gamma_{th}}{\overline{\gamma}}} - \mu_i}{\eta_i}\right)\right], \quad (11)$$

Performance Analysis | Results

$$\overline{\mathcal{C}} \approx \frac{B}{\ln 2}\left[\ln\left(1+\mathbb{E}\left[\gamma\right]\right) - \frac{\mathbb{E}\left[\gamma^2\right] - \mathbb{E}^2\left[\gamma\right]}{2\left(1+\mathbb{E}\left[\gamma\right]\right)^2}\right], \tag{12}$$

$$P_s\left(E\right) = \frac{1}{\pi}\int_0^{\frac{(M-\mathbf{1})\pi}{M}} \prod_{k=\mathbf{1}}^{L} M_{\gamma_k}\left(\frac{\sin^2\left(\frac{\pi}{M}\right)}{\sin^2\left(\theta\right)}\right) d\theta, \tag{13}$$

Performance Analysis | Simulation Results

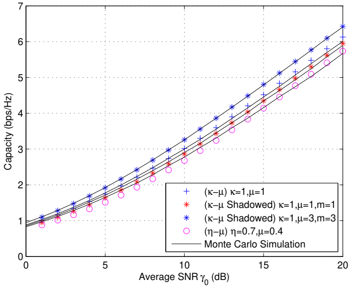

Figure: Analytical and simulated average channel capacity with B=$\frac{1}{2}$.

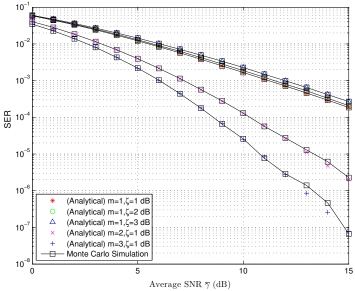

Figure: Analytical and simulation SER of 2-branch MRC receiver with BPSK for NL and RL fading channels.

The $\mathcal{MG}$ Distribution

- Here we approximate the SNRs of fading models by the $\mathcal{MG}$ distribution, resulting in the following:

The $\mathcal{MG}$ distribution

$$f_\gamma(x) = \sum_{i=1}^{K} \frac{\alpha_i}{\overline{\gamma}} \left(\frac{x}{\overline{\gamma}}\right)^{\beta_i - 1} \exp\left(-\zeta_i \frac{x}{\overline{\gamma}}\right), \tag{14}$$

where K denotes the number of mixture components, α_i, $i = 0, .., K$, is the mixing coefficient of the ith component having the constraints $0 \leq \frac{\alpha_i \Gamma(\beta_i)}{\zeta_i^{\beta_i}} \leq 1$ and $\sum_{i=1}^{K} \frac{\alpha_i \Gamma(\beta_i)}{\zeta_i^{\beta i}} = 1$. The scale and shape parameters of the ith component are β_i and ζ_i, respectively.

Expectation-Maximization

Original Problem formulation

The observed vector is the SNR, which we call $\boldsymbol{x} = \{x_1, \ldots, x_N\}$.

$$\begin{aligned} \theta_{MLE} &= \arg\max_{\theta\in\Theta} \mathbb{L}_{(\mathcal{MG})}(\theta|\boldsymbol{x}, K) \\ &= \arg\max_{\theta\in\Theta} \sum_{j=1}^{N} \ln\left[\sum_{i=1}^{K} \alpha_i x_j^{\beta_i - 1} \exp(-\zeta_i x_j)\right]. \qquad (15) \end{aligned}$$

- Unlike in the MoG, the $\mathbb{M}$-step does not have closed-form estimates.

Expectation-Maximization

EM treatment to the $\mathcal{MG}$ distribution

- $\mathbb{E}$-step: Compute: $\tau_{ij}^{(t)} = \frac{\alpha_i \phi(x_j|\beta_i,\zeta_i)}{\sum_{l=1} \alpha_l \phi(x_j|\beta_l,\zeta_l)}$.
- $\mathbb{M}$-step: Compute: $\alpha_i^{(t+1)} = \frac{1}{N} \sum_{j=1}^{N} \tau_{ij}^{(t)}$.
    - As for β_i, ζ_i coefficients, they are approximated directly using non-linear approximation method, namely Newton-Raphson algorithm.
    -

Expectation-Maximization | Analysis

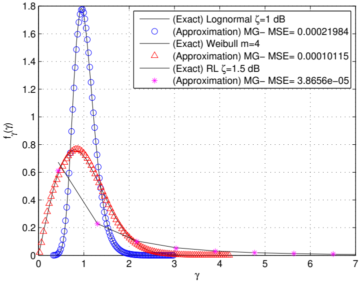

Figure: Approximation of instantaneous SNR distribution of Lognormal, Weibull, and RL for $M = 0$ dB.

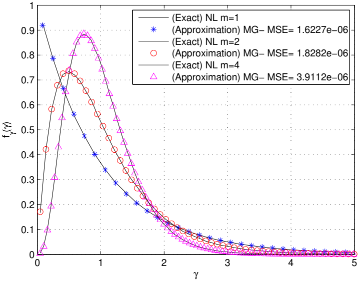

Figure: Approximation of instantaneous SNR distribution of several scenarios of NL distributions for $M = 0$ dB, $\zeta = \frac{1}{2}$ dB, with varying m.

Fixed-gain dual-hop relaying scenario

- Consider a dual-hop amplify-and-forward (AF) relaying scenario such that

$$\gamma_{end-to-end} = \frac{\gamma_{SR_1}\gamma_{R_1D}}{\gamma_{R_1D} + U},$$

where $U = \frac{1}{G^2 N_{01}}$ is a fixed-gain constant.

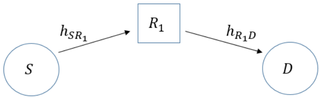

Figure: Fixed-gain dual-hop cooperative communication system.

Raw Moments

- To calculate the raw moments of composite fading channels in such system is intricate. However, with the $\mathcal{MG}$ distribution:

$$\mathbb{E}[\gamma^n] = \int_0^\infty \int_0^\infty \left(\frac{\gamma_1\gamma_2}{U+\gamma_2}\right)^n f_{\gamma_1}(\gamma_1)\, f_{\gamma_2}(\gamma_2)\, d\gamma_1 d\gamma_2, \qquad (16)$$

$$\mathbb{E}[\gamma^n] = \sum_{j=1}^{K} \alpha_{1j}\, \rho^n \frac{\Gamma(n+\beta_{1j})}{\zeta_{1j}^{n+\beta_{1j}}} \sum_{k=1}^{K} \frac{\alpha_{2k}}{\rho_2^{\beta_{2k}}} \frac{U^{\zeta_{2k}}}{\Gamma(n)}\, G_{2,1}^{1,2}\left(\begin{matrix} 1, 1+\beta_{2k} \\ n+\beta_{2k} \end{matrix} \middle| \frac{\rho_2}{U\zeta_{2k}} \right) \qquad (17)$$

Simulation Results | Average Channel Capacity

- Interesting Scenario: $|h_{SR_1}| \sim$ Weibull distribution with $m = 4$, and $|h_{R_1D}| \sim$ NL distribution with $(m = 4, \zeta = 2\,\mathrm{dB})$.

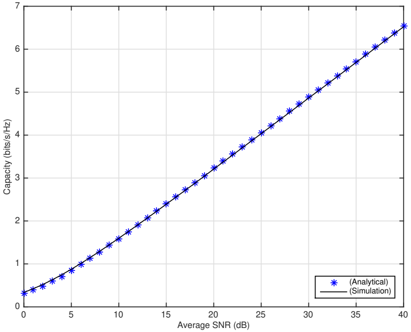

Figure: Average channel capacity for the selected scenario with $U = 0.5$,

Energy Detection Performance

- Cognitive radios came as a viable solution to mitigate the spectrum scarcity.
- Here we are concerned with the performance of the energy detector (ED) in generalized and composite fading channels.
  - The literature only offers a semi-analytic solution for the NL.
  - The $\mathcal{K}$ and K_G distribution is widely utilized to study the ED performance over RL channels.
- Here we utilize the $\mathcal{MG}$ distribution to study the ED performance.

Energy Detection Performance

- Goal is to study the detection and false-alarm probabilities in $\mathcal{MG}$-based fading channels.
- We consider square-law combining (SLC) and square-law selection (SLS) diversity schemes.
  - We derived the effective effective pdf under SLC, $f_{\gamma,\Sigma}$.

Impulsive Noise | Introduction

- Most of contributions in literature assume white Gaussian noise.
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Impulsive Noise | Introduction

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  - Ignoring the impact of impulsive noise caused by atmospheric, man-made partial discharge, switching effect, and electromagnetic interference.
- Among many models advocated to characterize impulsive noise, we adopt the Middleton Class-A (MCA) and ϵ-mixture noise models.
- Existing literature: Almost all works on impulsive noise considers multipath fading or shadowing alone.

MCA and ϵ-mixture Models

Middleton's Class-A Model

$$f_n(x) = \sum_{k=0}^{\infty} \Pr(T = k) f_{n|T=k}(x|k) \qquad (18)$$
$$= \sum_{k=0}^{\infty} \frac{e^{-A}A^k}{k!\sqrt{2\pi\sigma_k^2}} \exp(-\frac{x^2}{2\sigma_k^2}),$$

where A is the impulsive index that describes the average number of impulses during some interference time, $\sigma_k^2 = \frac{kA^{-1}+\Gamma}{1+\Gamma}\sigma^2$, $\lambda = \frac{\sigma_g^2}{\sigma_i^2}$ is the Gaussian Factor, which resembles the ratio of the variances of the background Gaussian component the impulsive component.

MCA and ϵ-mixture Models

ϵ-Mixture Model

$$f_n(x) = \frac{1-\epsilon}{\sqrt{2\pi\sigma_g^2}} \exp(-\frac{x^2}{2\sigma_g^2}) + \frac{\epsilon}{\sqrt{2\pi\sigma_i^2}} \exp(-\frac{x^2}{2\sigma_i^2}). \quad (19)$$

where ϵ denotes the fraction of time for which the impulsive noise occurs, with $0 < \epsilon < 1$. The ratio of the variances of the impulsive component to the Gaussian component is given by $\xi = \frac{\sigma_i^2}{\sigma_g^2}$. Here the power of n is given by $\sigma^2 = \frac{N_0}{2} = (1-\epsilon)\sigma_g^2 + \epsilon\sigma_i^2$.

- Note that the truncated two-term MCA model is a subset of the ϵ-mixture noise model and not the other way round.

Performance Analysis

Consider a Single-input-multiple-output communication scenario.

- Again here we consider the $\mathcal{MG}$ distribution.
- We derived the the following:
  - Analytical Pair-wise error probability (PEP) expressions with MRC and SC.
  - Analytical Average channel capacity expressions with MRC and SC.

Simulation Results

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Figure: SEP of BPSK with 4-MRC and 2-SC schemes for various $M\mathcal{G}$ based fading channels with MCA Noise of $\lambda, A = 0.1$, and $\dot{C} = 10$.

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Figure: SEP of BPSK with MRC scheme for NL fading with MCA Noise of $\lambda = 0.1$, $A = (0.1, 0.3, 0.9)$, and $\dot{C} = 10$.

Conclusions

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- We utilized the vanilla EM and VB frameworks, and advanced variants could be better.
- Although our approximation methodology was applied to single fading channels, it can be applied to *fading scenarios*.

Acknowledgments

- Advisors:
  - Prof. Jie Liang and Prof. Sami Muhaidat.
- Committee:
  - Prof. Paul Ho and Prof. Rodney G. Vaughan.
- Collaborators and Friends:
  - Prof. George Karagiannidis, Prof. Imtiaz Ahmed, Prof. Paschalis Sofotasios, Bassant Selim, Ahmed Al Hammadi, Koos van Nieuwkoop and Xiao Luo.
- Courses:
  - Prof. Ivan Bajic, Prof. Greg Mori, Prof. Faisal Beg, Prof. Paul Ho, and Prof. DanielLee.
- My lab mates, and the school of engineering science..

Q&A

Questions and Answers