



A Unified Approach for Representing Wireless Fading Channel using EM-based Mixture of Gamma Distributions

Omar Alhussein*, Sami Muhaidat^{†‡*}, Jie Liang*, and Paul D. Yoo[†].

Presented by: Ehab Salahat[†].

*School of Engineering Science, Simon Fraser University, BC, Canada. †Khalifa University of Science Technology and Research, Abu Dhabi, UAE. ‡Centre for Communication Systems Research (CCSR), University of Surrey, Guildford, United Kingdom.

Globecom 2014.

Broadband Wireless Access Workshop | Globecom 2014.

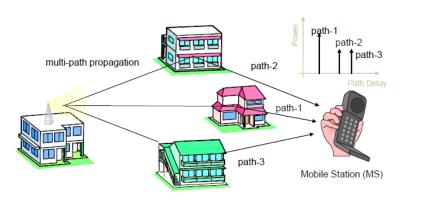
Dec 2014.

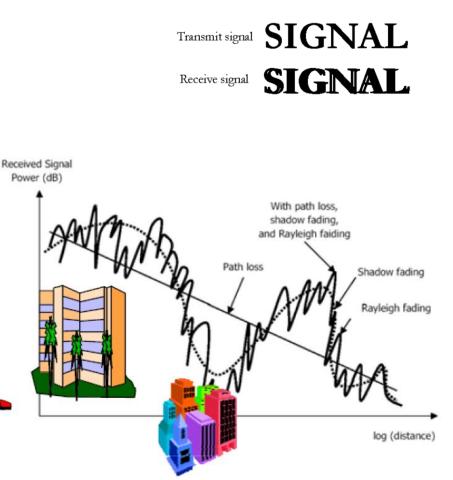
Outline

- Introduction | Literature Review
 - Physical Channel Modeling.
 - Composite Fading Channels.
- Proposed Approach
 - Expectation-Maximization Algorithm.
 - Model Analysis Comparisons.
- Performance Analysis | Fixed Gain Relaying
 - Fixed Gain Relaying Scheme over Generalized Fading.
 - Raw Moments, Amount of Fading, Capacity.
 - Simulation Results.
- Conclusions

Outline

- Physical Channel Modeling
 - Path Loss
 - $P_t \propto \frac{1}{d^n}$
 - Shadowing Effect
 - Lognormal Distribution
 - Multipath Fading Effect
 - Rayleigh, Nakagami-m, Weibull- β
 - Rician, etc.





Introduction | Literature Review

- Composite Fading Environments
 - We focus on Nakagami-m/Lognormal Fading.
 - Shadowing: Lognormal.

$$- f_L(\sigma) = \frac{\lambda}{\sqrt{2\pi}\sigma\zeta} e^{-\frac{(10\log_{10}\sigma - M)^2}{2\zeta^2}}$$

– Multipath: Nakagami-m, Rician, Weibull.

$$- f_N(\alpha|\sigma) = \frac{m^m}{\gamma_0^m \Gamma(m)} \gamma^{m-1} e^{-\frac{m\gamma}{\gamma_0}}$$

Composite Envelope

$$- f_{\alpha}(\alpha) = \frac{\lambda m^{m}}{\Gamma(m)\sqrt{2\pi\zeta}} \int_{0}^{\infty} \frac{x^{m-1}}{\sigma^{m+1}} e^{-\frac{mx}{\sigma^{2}}} e^{-\frac{(10\log\sigma - M)^{2}}{2\zeta^{2}}} d\alpha$$



Introduction | Literature Review

- Composite Fading Environments
 - Use of Moment Matching Methods.
 - K and K_G Distributions.
 - Replace Lognormal by Gamma Distributions, and solve.
 - Contains modified Bessel Function of second type, as

$$- f_{\alpha}(\alpha) = \frac{4}{\Gamma(\nu)} \left(\frac{\nu}{w}\right)^{\frac{\nu+1}{2}} \alpha^{\nu} K_{\nu-1}\left(\sqrt{\frac{4\nu}{w}} \alpha\right)$$

- RIGD and G Distributions.
 - Replace lognormal by Inverse-Gaussian and Solve.
 - Comparable Complexity with the Former, written as

$$- f_{\alpha}(\alpha) = \frac{4m^{\frac{\beta+1}{2}}}{\Gamma(m)\Gamma(k)\Omega^{\frac{\beta+1}{2}}} \alpha^{\beta} K_{\nu}\left(2\left(\frac{m}{\Omega}\right)^{\frac{1}{2}}\alpha\right)$$

Introduction | Literature Review

- Composite Fading Environments
 - Mixture Gamma Distribution [2011, Atapattu et al.]

•
$$f_{\alpha}(\alpha) = \frac{\lambda m^{m}}{\Gamma(m)\sqrt{2\pi\zeta}} \int_{0}^{\infty} \frac{x^{m-1}}{\sigma^{m+1}} e^{-\frac{mx}{\sigma^{2}}} e^{-\frac{(10\log\sigma - M)^{2}}{2\zeta^{2}}} d\alpha$$

Used Gauss-Quadrature Methods (Moment Matching).

•
$$f_{\gamma}(\gamma) = \sum_{i=1}^{C} \omega_i \left(\frac{\gamma}{\gamma_0}\right)^{\beta_i - 1} \exp\left(-\zeta_i \frac{\gamma}{\gamma_0}\right)$$

- Approximates:
 - Nakagami-m, Rayleigh, , η_{μ} , κ_{μ} , ...
 - Nakagami/Lognormal, Rician.

Not General for all channels

Introduction | Literature Review

- Approximation Methodology: EM Algorithm
 - Adopt **Mixture Gamma** Distribution.
 - Maximize Log-likelihood estimates via the use of Expectation-Maximization (EM) Algorithm.
 - Coined by Dempster *et al.* in 1977.
 - Iterative solution to intractable Maximum Likelihood Estimation (MLE) problems.
 - Pros:
 - Automated (Unsupervised Algorithm).
 - Proven not to get worse as it iterates by.
 - Cons:
 - Might get stuck in a local maxima. Though, works well in practice.

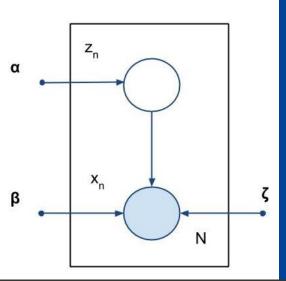
Adopted Approach | EM

- Approximation Methodology:
 - Let the j^{th} entry of an observed SNR vector $X = (x_1, x_2, ..., x_j, ..., x_N)$ be regarded as **incomplete** data.
 - Assume there exist hidden variable (Z), where $Pr(z_n = i) = \alpha_i$.
 - Assume that the marginal distribution X follows a Mixture Gamma (MG) distribution

$$-f_{\theta}(x_{j}) = \sum_{i=1}^{C} \alpha_{i} \phi_{i}(x_{j}; \beta_{i}, \zeta_{i})$$

$$where, \phi_{i}(x_{j}; \beta_{i}, \zeta_{i}) = x^{\beta_{i}-1}e^{-\zeta_{i}x}$$

• Goal: Maximize Log-likelihood - maximize $L(\theta) = \sum_{j=1}^{N} f_{\theta}(x_j)$.



Adopted Approach | EM

- Approximation Methodology:
 - $L(\theta)$ maximized iteratively through EM.
 - Consists of Two Main Steps:
 - Expectation Step: Compute Posterior Probability

$$- \tau_{ij}^{(t)} = \frac{\alpha_i \phi_i(x_j, \theta)}{\sum_i \alpha_i \phi_i(x_j, \theta)}$$

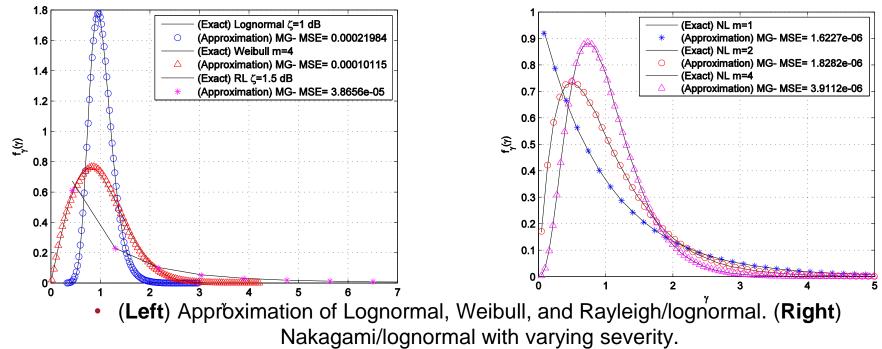
Maximization Step:

$$- \alpha_i^{(t+1)} = \frac{1}{n} \sum_{j=1}^n \tau_{ij}^{(t)}$$

- $\theta_i^{(t+1)} = [\zeta_i, \beta_i]$ are computed by maximizing the likelihood using the Newton-Raphson algorithm, using 'nlm' package in Software R.
- Iterate between Expectation and Maximization until convergence is reached, $\theta_i^{(t+1)} \theta_i^{(t)} < \delta$.

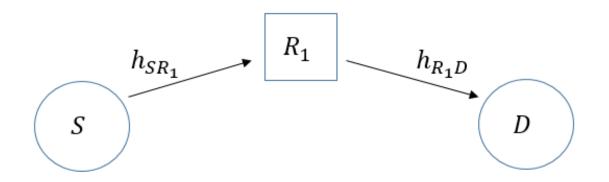
Adopted Approach | EM

- Approximation Results
 - May be used to other fading distributions.
 - mean square error (MSE) to validate accuracy.
 - Only two components is used, C = 2.



Adopted Approach | Model Analysis and Comparisons

- System Model
 - Consider a dual-hop Amplify-and-Forward (AF) cooperative scenario, as shown below.
 - h_{SR_1} , h_{R_1D} are *i.n.i.d.* and follow the generalized MG distribution.
 - The relay R_1 is a fixed-gain relay, with gain G.



Performance Analysis | Fixed Gain Relaying

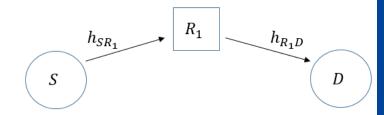
System Model

•
$$y_{SR_1}(t) = h_{SR_1}(t)x(t) + n_{SR_1}(t)$$

•
$$y_{R_1D}(t) = G h_{R_1D}(t) y_{SR_1}(t) + n_{R_1D}(t)$$

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

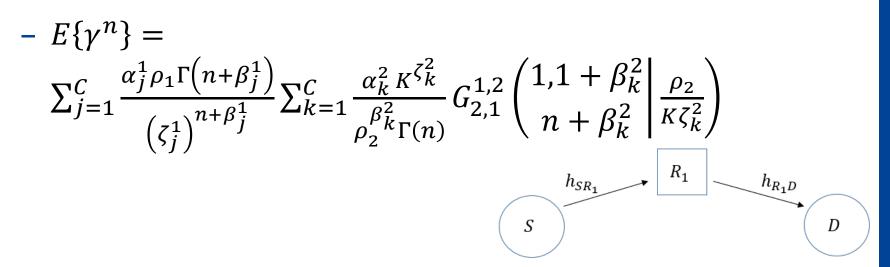
• $K = \frac{1}{G^2N_{01}}$ is fixed constant.



Current Work | Results

Raw Moments of end-to-end SNR

$$- E\{\gamma^n\} = \int_0^\infty \int_0^\infty \left(\frac{\gamma_1\gamma_2}{K+\gamma_2}\right)^n f_{\gamma_1}(\gamma_1) f_{\gamma_2}(\gamma_2) d\gamma_1 d\gamma_2$$
$$- f_{\gamma_i}(x) = \sum_{i=1}^C \frac{\alpha_i}{\rho} \left(\frac{x}{\rho_i}\right)^{\beta_i - 1} e^{-\frac{\zeta_i x}{\rho_i}}$$



Performance Analysis | Fixed Gain Relaying

- Amount of Fading
 - First Introduced by (Charash, 1979) as a measure of the severity of the fading channel.
 - Can be computed from first two moments.

•
$$AoF = \frac{E\{\gamma_{end-to-end}^2\} - (E\{\gamma_{end-to-end}\})^2}{(E\{\gamma_{end-to-end}\})^2}$$

Performance Analysis | Fixed Gain Relaying

- Average Capacity
 - Defined as the mean of the instantaneous mutual information (IMI).

•
$$C_{erg} = \frac{B}{\ln 2} E\{\ln(1 + \gamma_{end-to-end})\}$$

- Using Taylor Series of $\ln(1 + \gamma_{end-to-end})$ around $E\{\gamma_{end-to-end}\}$.

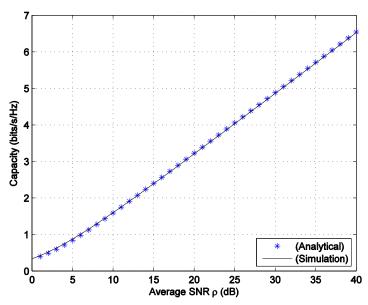
$$-\ln(1+\gamma) = \ln(1+E\{\gamma\}) + \sum_{w=1}^{\infty} \frac{(-1)^{w-1}(x-E\{\gamma\})}{w(1+E\{\gamma\})^w}$$

– Take Expectation of $\ln(1 + \gamma)$ and truncate to first two moments.

•
$$C_{erg} = \frac{B}{\ln 2} \left[\ln(1 + E\{\gamma_{end-to-end}\}) - \frac{E\{\gamma_{end-to-end}\} - E^2\{\gamma_{end-to-end}\}}{2(1 + E\{\gamma_{end-to-end}\})^2} \right]$$

Performance Analysis | Fixed Gain Relaying

- Average Capacity
 - h_{SR_1} follows Weibull distribution.
 - h_{R_1D} follows Nakagami-m/lognormal distribution.
 - Fixed Gain K=0.5.
 - Very accurate for whole operating SNR, with C = 2.



Performance Analysis | Fixed Gain Relaying

Conclusions

- We provided general framework to approximate any arbitrary fading distribution by presenting them as Mixture Gamma (MG) distribution.
 - Used Expectation-Maximization algorithm with Newton-Raphson maximization algorithm to maximize the loglikelihood estimates.
- Analyze and study performance analysis of dualhop fixed-gain AF cooperative scenario for noncomposite and composite fading distributions.

Conclusion and Future Work