

Project proposal: MATTEK9/10

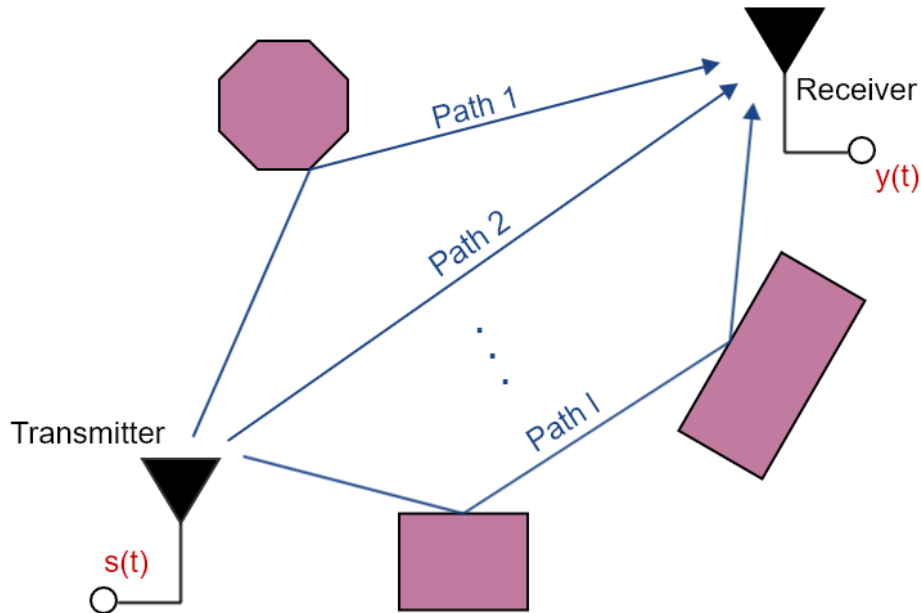
Calibration of radio channel model using approximate Bayesian computation

The design and analysis of wireless communication systems involve not only the knowledge about the transmitter, receiver and their corresponding antennas, but also about the environment that will interact with the transmitted signal. The propagation environment, or the medium, used to transmit information from the transmitting antenna to the receiving antenna is termed as the *radio channel*. Realistic modelling of the radio channel is imperative to the analysis of the performance of any wireless system. *Channel modelling* refers to the craft of creating a mathematical description of the radio channel. If the channel between the antennas is modelled accurately, the received signal can be obtained from the transmitted signal, which is the primary motive.

The receive signal, $y(t)$, can be modelled as a superposition of delayed and scaled versions of the transmitted signal, $s(t)$, (see figure) as

$$y(t) = \sum_l \alpha_l s(t - \tau_l),$$

where α_l and τ_l are the complex gain and time-delay of the l^{th} multipath component, respectively. A stochastic channel model considers these delays and gains as random variables and characterizes them using stochastic distributions/processes.



Multipath propagation.

For a model to be useful for simulation, it should be *calibrated*, i.e. its parameters should be estimated such that the model fits to the measurement data. Traditionally, this is done by maximizing the likelihood function of the data with respect to the parameters, or by finding the posterior distribution of

the parameters (in a Bayesian approach). In either case, access to the likelihood function is required. Unfortunately, the likelihood is not available for most stochastic channel models, therefore we need to employ likelihood-free inference techniques.

Potential solution

Approximate Bayesian computation (ABC) [1, 2] is an approach to perform (approximate) Bayesian inference for generative models without the need for specifying a likelihood function. ABC was first introduced in the field of population genetics in 1997 and since then it has been applied in various diverse fields such as ecology, atmospheric contamination, and cosmology, to name a few.

ABC relies on generating simulated data, y_{sim} from the some arbitrary parameter setting, θ^* , of the model, and compares it to the measurement data, y , in some distance metric ρ . If y_{sim} is “close” to y , then θ^* is accepted to be from the posterior distribution. That is, given observation y , repeat the following until N points have been accepted:

1. Draw θ^* from the prior distribution, $p(\theta)$
2. Simulate y_{sim} from the model, $p(y|\theta^*)$
3. Accept θ^* if $\rho(y_{\text{sim}}, y) < \epsilon$

Output: accepted samples $(\theta_1, \dots, \theta_N)$, forming an approximation of $p(\theta|y)$

The goal of this project is to apply an ABC method to calibrate a stochastic channel model, in particular, the Turin model [3]. In addition to the parameters of the Turin model, we would also like to estimate the line-of-sight (LOS) delay in the data. There exists more advanced ABC algorithms than the basic accept-reject algorithm described above [1, 2]. The selection of the particular ABC algorithm to implement lies with the students. There is also scope of expanding the project to study multi-input, multi-output (MIMO) channel models. There is access to channel impulse response data for this project.

Theoretical tools applied in the project

- Probability theory
- Stochastic processes
- Point process theory
- Bayesian inference
- Monte Carlo simulations
- Estimation theory

Project format

The project can be carried out individually or in a group, with the scope and goals being adapted accordingly.

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Bibliography

- [1] Brandon M. Turner and Trisha Van Zandt. “A tutorial on approximate Bayesian computation”. In: *J. Math. Psychol.* 56.2 (2012), pp. 69–85. DOI: 10.1016/j.jmp.2012.02.005.
- [2] Mark A. Beaumont. “Approximate Bayesian Computation in Evolution and Ecology”. In: *Annu. Rev. Ecol. Evol. Syst.* 41.1 (2010), pp. 379–406. DOI: 10.1146/annurev-ecolsys-102209-144621.
- [3] G. L. Turin et al. “A statistical model of urban multipath propagation”. In: *IEEE Trans. Veh. Technol.* 21.1 (1972), pp. 1–9. ISSN: 0018-9545. DOI: 10.1109/T-VT.1972.23492.