Learning Parameters of Stochastic Radio Channel Models from Summaries

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1st Post-IRACON Meeting
September 14-15, 2020

Model Calibration Problem

Aim: To fit a stochastic radio channel model $\mathcal{M}(\theta)$ (e.g. Saleh-Valenzuela, Propagation Graph, etc.) to channel impulse response measurements y

Calibration Problem: Estimate θ given data y

Classical estimation techniques require access to the likelihood function:

Maximum a Posteriori (MAP) estimate: $\hat{\theta}_{\text{MAP}} = \underset{\theta}{\operatorname{argmax}}\, f(y|\theta)p(\theta)$

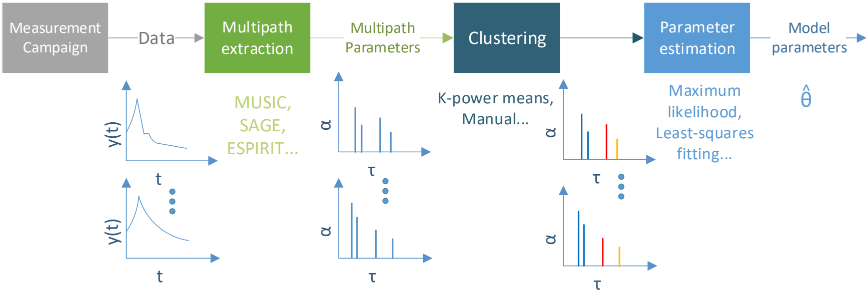
Maximum Likelihood (ML) estimate: $\hat{\theta}_{\text{ML}} = \underset{\theta}{\operatorname{argmax}}\, f(y|\theta)$

Minimum Mean Squared Error (MMSE) estimate: $\hat{\theta}_{\text{MMSE}} = \mathbb{E}\left[f(y|\theta)p(\theta)\right]$

Since we do not observe the multipath components (i.e. their delays, gains, etc.), the likelihood function $f(y|\theta)$ is intractable and cannot be evaluated numerically.

State-of-the-art Calibration Method

Calibration method followed by SV, COST 2100, WINNER, METIS, etc.:

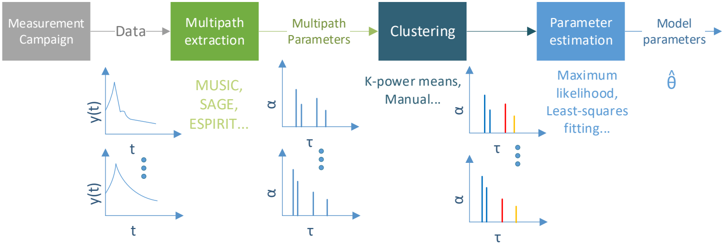


Drawbacks:

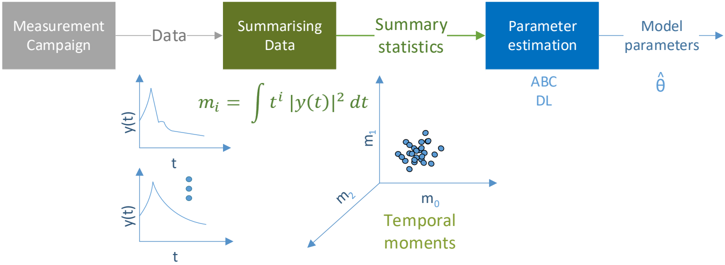
- Requires sophisticated algorithms (multipath extraction, clustering) which can be cumbersome to use due to a number of heuristic choices
- Prone to errors (e.g estimation artifacts, censoring effects)
- Overall performance of these algorithms are hard to investigate

Proposed Calibration Methods

Instead of using multipath components and clusters:



we use easy-to-compute summaries:



Proposed Calibration Methods

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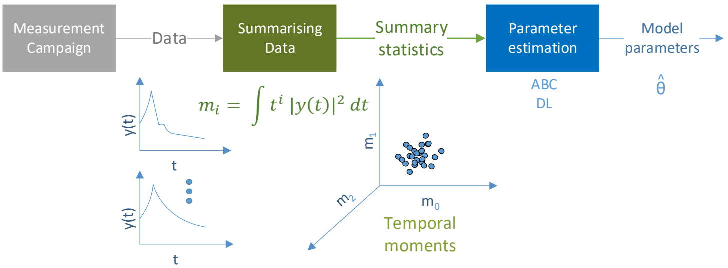


Advantages:

- Simpler processing chain
- Fit is based on explicit choice of summaries
- Easier to evaluate performance of the estimator
- Information on posterior is obtained (not only point estimates)

Approximate Bayesian Computation (ABC)

ABC is a likelihood-free inference method that permits sampling from the (approximate) posterior of a generative model[1].

Rejection ABC algorithm

- Sample $\theta^* \sim p(\theta)$
- Simulate data from model, $y \sim \mathcal{M}(\theta^*)$
- If $\rho\left(S(y), S(y_{\mathrm{obs}})\right) < \epsilon$, accept θ^*

Here $S(\cdot)$ is a vector of summary statistics and $\rho(\cdot,\cdot)$ is a distance measure.

With N accepted samples, we can approximate the posterior distribution:

$$p(\theta | \rho\left(S(y), S(y_{\mathrm{obs}})\right) < \epsilon) \approx p(\theta|y),$$

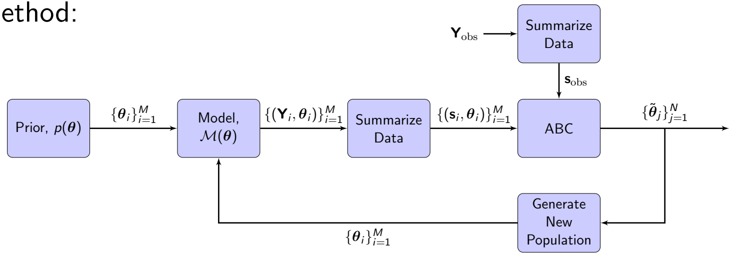
and can compute point estimates:

$$\hat{\theta}_{\mathrm{MMSE}} \approx \frac{1}{N}\sum_{i=1}^{N} \theta_i$$

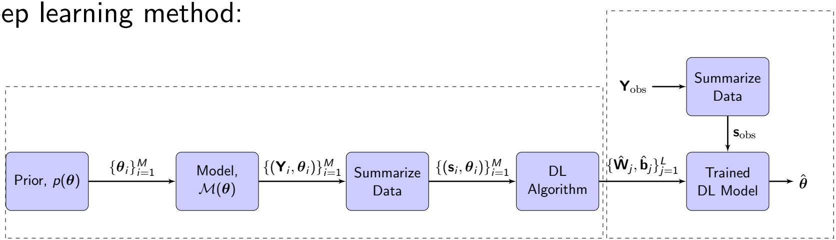
[1] M. A. Beaumont, Approximate Bayesian computation in evolution and ecology, Annu. Rev. Ecol. Evol. Syst., vol. 41, pp. 379406, dec 2010.

Proposed Likelihood-free Inference Methods

ABC method:



Deep learning method:



Simulation Experiment

- **Model:** Polarimetric Propagation model[2]
- **Parameters:**
  - Reflection gain, $g \sim \mathcal{U}(0,1)$
  - No. of scatters, $N_s \sim$ Uniform integers$[5,50]$
  - Probability of visibility, $P_{\text{vis}} \sim \mathcal{U}(0,1)$
  - Polarization ratio, $\gamma \sim \mathcal{U}(0,1)$
  - Noise variance, $\sigma_N^2 \sim \mathcal{U}(2 \times 10^{-10}, 2 \times 10^{-9})$
- **Summaries:**
  - Means and covariances of first three temporal moments:

$$m_k = \int t^k |y(t)|^2 \mathrm{d}t, \quad k = 0, 1, 2.$$

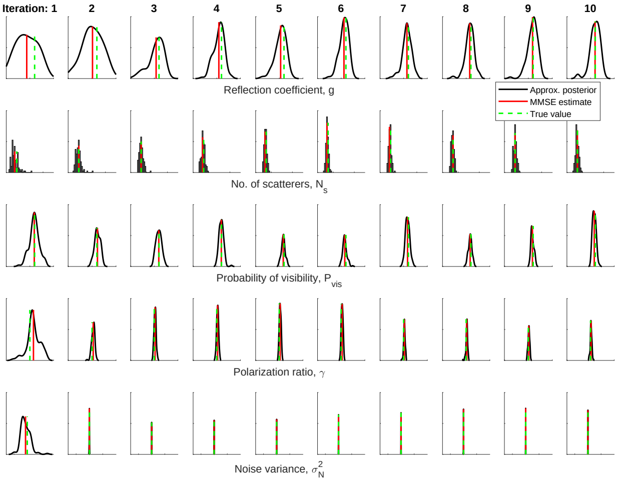
  - Cross-polarization ratio

$$\mathrm{XPR} = \frac{1}{2}\left[\frac{\mathbb{E}[m_0^{vv}]}{\mathbb{E}[m_0^{vh}]} + \frac{\mathbb{E}[m_0^{hh}]}{\mathbb{E}[m_0^{hv}]}\right]$$

[2] R. Adeogun, T. Pedersen, C. Gustafson, and F. Tufvesson,Polarimetric Wireless Indoor Channel Modelling Based on Propagation Graph,IEEE Transactions on Antennas and Propagation,vol. 67, no. 10, 2019.

Simulation Results using ABC

Approximate marginal posteriors after each iteration:

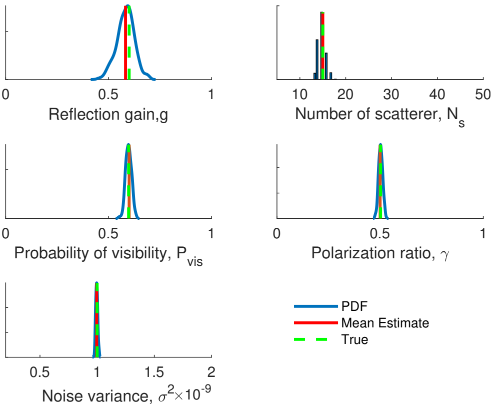


- Distribution of samples converge around the true value.
- Width of posterior is different for different parameters.
- Some parameters converge faster than others.

Simulation Results using Deep Learning

Settings: 2 hidden layers, 20 neurons per layer

Distribution of parameter estimates obtained after 200 estimator runs:



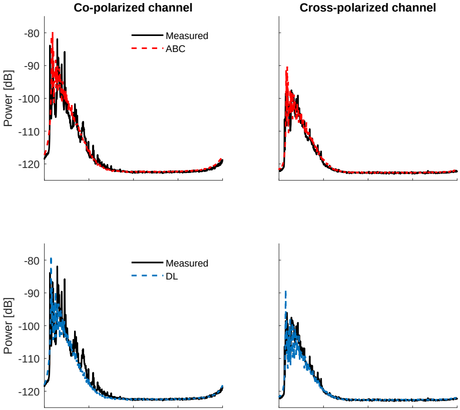
Observations:

- The parameters are estimated accurately.
- The uncertainty in estimates is fairly small.

Application to Measured Data

We apply the proposed methods on MIMO measurements from Gustafson et al., 2016[3].

- Environment: small conference room of dimension $3m \times 4m \times 3m$
- Frequency range: 58 GHz to 62 GHz
- 25×25 planar array, leading to 625 channel realizations
- 801 frequency samples
- Frequency separation: 5 MHz



[3] Carl Gustafson, David Bolin, Fredrik Tufvesson, Modeling the polarimetric mm-wave propagation channel using censored measurements, IEEE GLOBECOM, 2016.

Conclusions

- The proposed machine learning methods based on ABC and DL are able to accurately calibrate stochastic radio channel models, in particular the PG model.
- The methods by-pass any intermediate step of extracting the multipath components and require no additional information or post-processing.
- Availability of pseudocodes and libraries make the proposed methods easy to implement compared to the state-of-the-art approach.
- The performance of the proposed methods is easy to evaluate, as opposed to the multi-step approach.
- The choice of summaries is crucial in estimating the parameters, and the uncertainty in the estimates decreases with informative summaries.
- **Coming soon:** Generic ABC method for calibrating different channel models.