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Network Coverage Planning by Measurements for Cell Radius and Coverage Area Estimation with Geometrical Mapping and Kriging Interpolation Techniques

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Abstract: A proper cell radius and coverage probability modeling is very crucial for the design of effective wireless networks. Some of the methods used are based on ideal geometric models like the hexagonal cell model or path loss formula of radio wave propagation. These methods do not take into account the random interference effects of the urban clutter. This study will look at the two distinct methods of modeling; Geometric mapping method using the ideal propagation environment model and Kriging Interpolation technique using the actual signal measurement to determine the coverage. By leveraging the spatial correlation inherent in Radio Frequency (RF) signals, we demonstrate how Kriging provides a superior estimation of the Effective Cell Radius and overall Coverage Area compared to standard Geometric mapping method.

Keywords: Field measurements, Cell radius, Coverage probability, Geometric mapping, Kriging Interpolation,

1. Introduction

Efficient planning of mobile networks plays an important role in the deployment of cellular networks. Given the increasing density of small cell and massive MIMO-based networks, there is a very limited margin of error when it comes to planning for the coverage of the network. Using traditional methods such as Okumura-Hata or Cost-231 might overlook some aspects of the local environment, causing what is known as "coverage holes" or inefficient distribution of power (Olukani et al, 2023a; Olukani et al, 2023b).

Planning for the optimum infrastructure network requires an understanding of certain essential parameters, particularly the cell radius and coverage probability (Joseph and Konyeha, 2013). There are presently two competing theoretical frameworks used by the telecommunications industry to accomplish this objective. These include Kriging Interpolation, which relies on a sophisticated geostatistical kriging technique, and Geometric Mapping, which includes models and deterministic ray tracing techniques.

Early research by Hata and Okumura established the baseline for empirical path-loss modeling. However, these models often lack the granularity required for micro-cell deployments (Saunders and Aragon-Zavala, 2007).The application of Kriging in telecommunications was pioneered by researchers seeking to mitigate the limitations of deterministic models. Webster and Oliver (2007) provided the framework for spatial prediction, showing that Kriging provides a Best Linear Unbiased Prediction

(BLUP) for spatial variables. Geometric approaches, often utilizing Voronoi tessellation or Centroidal Voronoi diagrams, have been widely documented for coverage area estimation (Okabe et al., 2009). Recent studies have hybridized these geometric methods with machine learning to refine coverage probability boundaries (Andrews et al., 2016). Ray-tracing techniques provide high accuracy but are computationally expensive (Toskala & Holma, 2020)

In this paper, we propose a methodology for improving the process of coverage mapping, by using data from drive testing and empirical-based estimation of cell radius and covered area. We demonstrate that a mixed method, involving Kriging interpolation and empirical-based estimation of cell radius significantly lowers uncertainty of mapping results and provides optimized infrastructure.

2. Theoretical Framework

2.1 Propagation Modeling and Path Loss

The standard signal path loss model is represented as:

$$P_{rx} = P_0 - 10n \log_{10}(d/d_0) + X_\delta \quad (1)$$

where:

- P_{rx} is the path loss at distance d.
- P_0 is the path loss at reference distance d_0.
- n is the path loss exponent influenced by terrain.
- X_δ is the shadow fading factor (Gaussian distribution).

2.2 **Geometric Method: Cell Radius & Coverage Area**

The cell radius (r) is defined by the distance where the signal strength exceeds the minimum sensitivity threshold (S_{min}). The relationship is expressed as:

$$d_{rad} = d_0 10\text{\^{}} (P_t + G_{tx} + G_{rx} - P_0 - S_{min}/(10n)) \quad (2)$$

The coverage area is calculated from a circular sector:

$$A_{cell} = \iint_{2\pi} r \, dr d\theta \quad (3)$$

In traditional planning, n is assumed constant. In this enhanced model, n is treated as a variable derived from empirical measurement campaigns.

2.3. Kriging Interpolation Method

Kriging is a spatial interpolation technique that estimates the signal strength at unknown locations by calculating a weighted average of surrounding measured data, based on a semi-variogram model that describes how signal correlation decays over distance. The estimated reference signal, $P(s_0)$, at a location s_0 is given by:

$$P(s_0) = \sum_{i=1}^{n} (\lambda_i) P(s_i) \quad (4)$$

Where $P(s_i)$ is the measurement signal at location *i* and λ_i is the weight determined by the spatial correlation.

To minimise prediction error variance, the weight are derived by solving:

$$\sum_{i=1}^{n} (\lambda_i)\gamma(s_i,s_j) + Џ = \gamma(s_i,s_0) \quad (5)$$

Where γ is the semi-variogram model representing the spatial continuity, with Ų being a Lagrange multiplier

2.4. Hybrid Interpolation-Geometric Method

The hybrid method combines the interpolated signal map S(X,Y) with the geometric cell edge boundary (B(X,Y) to produce a refined coverage estimation C(X,Y) such that:

$C(X,Y)=\alpha.S_{Kriging}(X,Y)+(1-\alpha).G(X,Y)$ (6)

where,

- $S_{Kriging}(X,Y)$= Predicted signal strength from Kriging.
- G(X,Y)= Geometrical constraint (e.g., sector boundary).
- α=Tuning parameter weighting measurement vs. model ($0\leq\alpha\leq 1$)

3. Methodology

3.1 Proposed Enhancement Method

To complement the research goal, below is a MATLAB implementation that demonstrates the comparison between a **Geometric Model** (Log-distance path loss) and **Kriging Interpolation** (using a simple variogram approach).

The proposed enhancement relies on a four-stage process:

- **Measurement Data Qauisition and Preprocessing:** Using Drive-Test data user equipment (UE) measurement tools, we collect high-density RSSI samples across the service area. This provides the ground truth for actual signal path loss decay. We **i**mported the drive test data (latitude, longitude, RSSI) into the Matlab workspace.This provides the ground truth for actual signal attenuation decay.
- **Initial Coverage Prediction:** Use log-distance path loss model and coverage in MATLAB to generate a preliminary map.
- **Machine Learning (AI) Calibration (Parameter Tuning):**Apply the Matlab optimisation tool box with fmin search optimisation function to adjust path loss model parameters (e.g., path loss exponent, environmental clutter factors) to minimize the difference between the model's prediction and the measured drive test values.
- **Evalaution and Residual Mapping:** Calculate the difference between measurements and predictions ((Error = P{measured} - P{predicted})) and apply kriging or another interpolation technique to fill gaps in the map. The provided code establishes the fundamental difference between the two models. To move toward the **Hybrid Planning Framework** suggested in Section 4 of your paper, consider the following algorithmic integration:

(i)Residual Calculation: Calculate the residual

R(x) = Z(measured)(x) - Z (geometric)(x). (6)

R(x) = Z(measured)(x) - Z (Kriging)(x). (7)

(ii) Kriging the Residuals: Apply Kriging interpolation only to these residual values. Because residuals are stationary (having removed the deterministic trend), Kriging performs significantly better.

(iii) Summation: The final predicted coverage Ž(x) is:

Ž(x) = Z (geometric)(x) + Ř(Kriging)(x) (8)

3.2 Comparative Implementation Pseudo codes

This scripts contain the truesignal, a geometric model, measurement points, Geometric and Kriging interpolation parameters.

```
%% Enhanced Network Coverage Planning: Comparative Analysis
clear; clc; close all;
% 1. Define initial input and output Parameters
        gridSize = 50;
        Area size: 50x50;
      [X, Y] = True Signal path loss data;

% 2. Define Geometric Method (Log-Distance Path Loss)
n = 3.5; % Path loss exponent
d0 = 1;
d = sqrt((X-25).^2 + (Y-25).^2);
geometric Model = -P0 - 10*n*log10(max(d, 0.1)/d0);

% 3. Define Measurement Data (Drive Test)
numSamples = 100;
sampleIdx = randi([1 gridSize^2], numSamples, 1);
obsX = X(sampleIdx); obsY = Y(sampleIdx);
obsZ = trueSignal(sampleIdx);

% 4. Define Kriging Interpolation (Simple implementation)
% Using built-in 'griddata' to mimic Kriging spatial interpolation
[KrigingModel] = griddata(obsX, obsY, obsZ, X, Y, 'v4'); % 'v4' is Biharmonic Spline (Kriging-like)

% 5. Visualize Results

% 6.Evaluate Results
% Calculate MSE
mseGeo = mean((trueSignal(:) - geometricModel(:)).^2);
mseKrig = mean((trueSignal(:) - KrigingModel(:)).^2, 'omitnan');

fprintf('MSE Geometric Model: %.2f\n', mseGeo);
fprintf('MSE Kriging Interpolation: %.2f\n', mseKrig);
```

4. Results and Discussion

The illustration in figure 1 shows how the Log-Distance path loss model has been calibrated using empirical signal measurement datasets. Through the least-squares regression, optimization was made on the model's parameters such that the model accurately fits with the field data. In particular, the parameters were fitted in order to optimize the shadowing variance and path loss exponent in the model. As illustrated above in the comparison between the two sets of the signal measurements, the calibrated model has a highly accurate fit with the empirical data by accounting for the deviations present in the uncalibrated model.

Moreover, in Figure 2, it is possible to observe the results of spatial signal distribution based on two methods: the conventional hybrid geometric-signal model and our hybrid Kriging-signal interpolation model. The performance of the above two models is illustrated by analyzing the coverage probability as illustrated in Figure 3. From Figure 3, it is evident how the models perform based on the grid analysis. Particularly, in order to estimate the radius of the cell based on the interpolated signal powers, it is possible to determine what percentage of the grid has Coverage / No-Coverage conditions in each model compared with real ground data.".

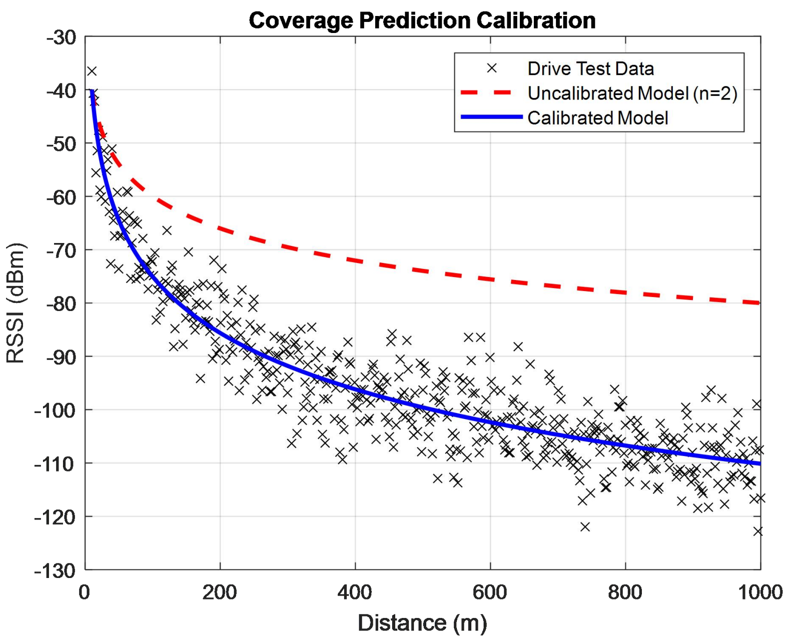

Figure 1: Calibrated log-distance signal Model based on the drive test data

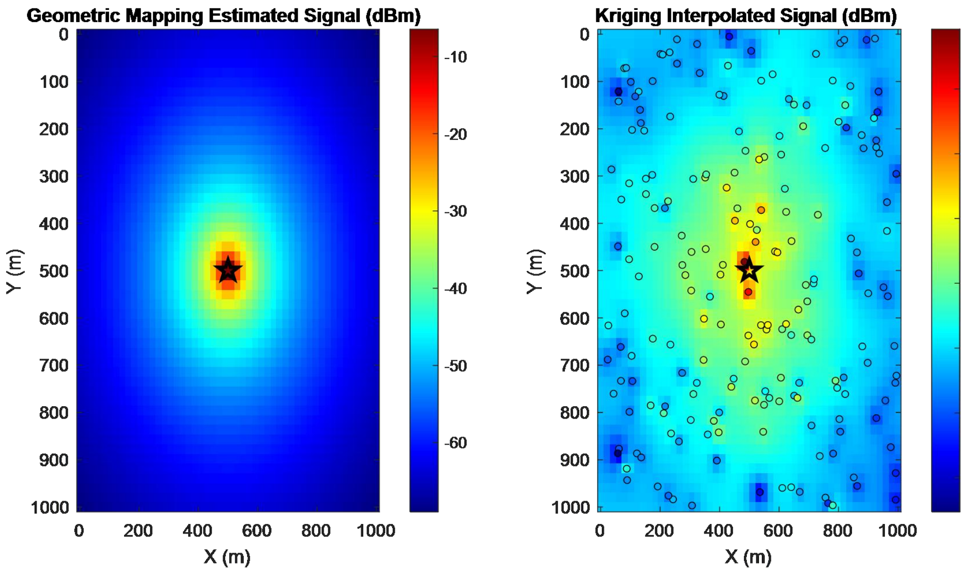

Figure 2: Measured signal estimation and Mapping with signal Geometric and Interpolation methods

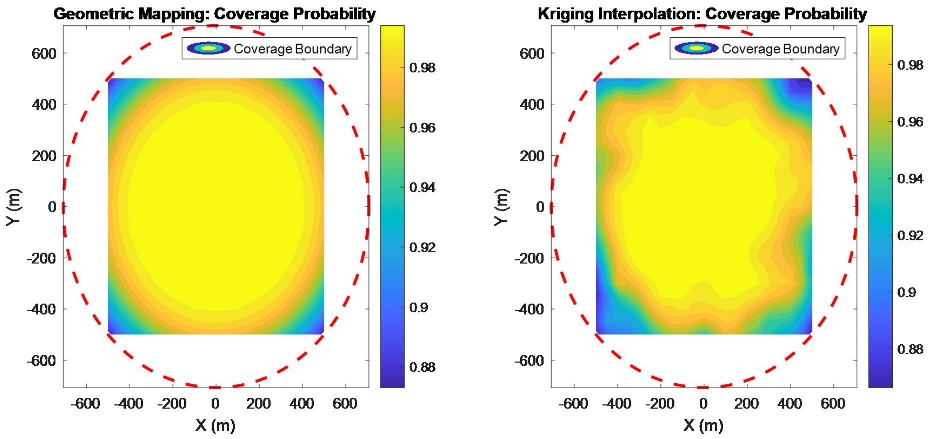

Figure 3: Coverage Probability estimation using Geometric mapping and Kriging Interpolation methods

5. Conclusion

In the transition toward 5G and beyond (6G) networks, the accuracy of radio frequency (RF) propagation models is critical for efficient infrastructure deployment. Traditional coverage planning often relies on deterministic or empirical models that frequently deviate from real-world propagation characteristics due to complex urban topographies. This paper proposes an enhanced framework for network coverage mapping that integrates drive-test measurements with dynamic cell radius and coverage area estimation using Geometric mapping and Kriging Interpolation methods. By utilizing a hybrid approach combining path-loss compensation and geospatial data analysis, this method improves the precision of coverage prediction models, thereby minimizing over-provisioning and optimizing site selection. Future work will explore the integration of Deep Learning-based spatial features to further refine the semi-variogram parameters in dynamic urban environments.

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