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Spatial Interpolation based Cellular Coverage Prediction with Crowdsourced Measurements

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ABSTRACT

Coverage extension and prediction has always been of great importance for mobile network operators. For coverage extension, the empirical and analytical path loss models assist in better positioning of the infrastructure. However post-deployment coverage prediction can be more cost effectively enabled by crowdsourced measurements. Unlike drive testing, crowdsourced measurements along with spatial interpolation techniques can help generate coverage maps with less expense and labor. Using controlled measurements taken with commodity smartphones, we empirically study the accuracy of a wide range of spatial interpolation techniques, including various forms of Kriging, in different scenarios that capture the unique characteristics of crowdsourced measurements (inaccurate locations, sparse and non-uniform measurements, etc.). Our results indicate that Ordinary Kriging is a fairly robust technique overall, across all scenarios.

CCS Concepts

•**Networks** → **Network measurement; Mobile networks;**

Keywords

Cellular coverage prediction; crowdsourced mobile network measurement; spatial interpolation

1. INTRODUCTION

Prediction of network coverage is of vital importance to mobile network operators and service providers. Not only before but also after the deployment of network infrastructure, the level of network coverage provided to various parts of region under consideration is measured on a regular basis. This regular check is to determine any coverage holes produced due to construction of new buildings, highways or changes in customer residential preferences. In order to maintain customer market and fulfil obligations towards the regulatory authorities, such as FCC and Ofcom, the coverage holes thus diagnosed are dealt with either by changing antenna tilt, its height, power level or deployment of new base stations etc.

To extend coverage and to deploy additional infrastructure, the traditional approach is to use analytical propagation models (e.g., Okumura-Hata, Longley-Rice irregular terrain model) [1]. Some empirical measurements may be needed for this approach and in developing the underlying models themselves (e.g., Okumura-Hata) to obtain fitted constants and for adjustments/corrections of model equations. However to optimize the coverage, in operational phase, this approach, exemplified by 3G coverage maps produced by Ofcom in [2], is inherently inaccurate. A relatively newer and potentially more accurate approach to coverage prediction and mapping is based on geostatistics (e.g., [3–5]). It involves strategically collecting measurements (referred to as spatial sampling) and use of spatial interpolation techniques to predict values at unobserved locations. This type of coverage estimation via measurements and interpolation is presented as an example application scenario of spatial big data in [6].

It is evident from the above description that both approaches to coverage prediction require measurements. Even to obtain measurements, there are two broad approaches. The traditional approach is drive testing (e.g., [7]), which is expensive, labor intensive and time consuming. A more recent approach referred to as crowdsourcing (e.g., [8–11]) exploits end-user mobile devices as measurement sensors and the natural mobility of people carrying them for cost-effective and diverse spatiotemporal monitoring of mobile networks. Also, crowdsourced measurements reflect user perceived mobile performance, as they are obtained from end-user devices. To avoid the expense of drive tests, 3GPP has also been developing a specification called Minimization of Drive Tests (MDT) [12] for use in UMTS and LTE networks. MDT is also a crowdsourcing approach involving end-user devices for collecting measurements.

In this paper, we empirically study the effectiveness of a wide range of spatial interpolation techniques, including the widely used Kriging methods, for coverage prediction in the context of crowdsourced measurements. Specifically,

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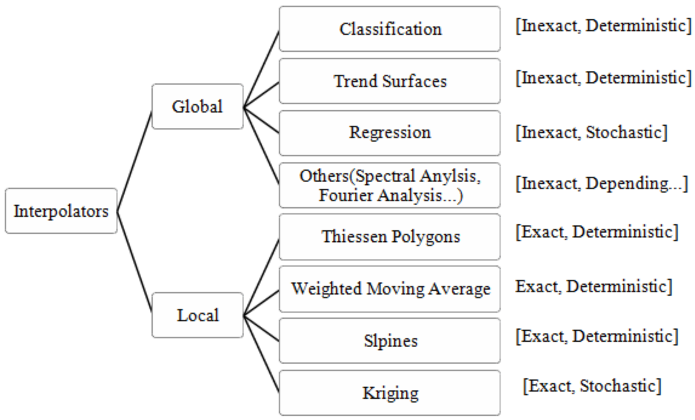

Figure 1: A taxonomy of spatial interpolation techniques based on [13].

crowdsourced measurements have certain unique characteristics, including: inaccurate locations of measurements; non-uniform and sparse set of measurements. We examine the impact of these different characteristics of crowdsourced measurements on the accuracy of spatial interpolation techniques, which has not been done before to the best of our knowledge. Our analysis results show that prediction error with spatial interpolation techniques is impacted by different crowdsourced measurement characteristics with Ordinary Kriging emerging as a fairly robust technique overall.

The rest of the paper is structured as follows. Next section provides a brief overview of different spatial interpolation techniques and discusses related work. Following sections, respectively, examine the impact of location inaccuracy, measurement distribution and density on the accuracy of different spatial interpolation techniques. Section 6 concludes the paper.

2. BACKGROUND

2.1 Spatial Interpolation Techniques

Pringle [13] presents a taxonomy of spatial interpolation techniques which we summarize in Figure 1. There are mainly two types of interpolation methods, i.e. global and local interpolators. The former use all the available data whereas the latter use only the information in the vicinity of the point being estimated. Interpolation methods can be exact or inexact. The predicted value of the exact interpolator is similar to the measured value; inexact interpolators remove this constraint and produce a smoother surface. Interpolation methods can be also categorized as deterministic or stochastic. Unlike deterministic, stochastic methods provide uncertainty estimates.

Below we outline the different spatial interpolation techniques considered in this paper.

- **Kriging** is a class of local interpolation techniques that are quite commonly used to address spatial prediction problems in the context of mining, hydrogeology, natural resources, environmental science, etc.. The basic idea of Kriging is to estimate data at a point based on regression of observed surrounding values of that point weighted according to the spatial correlation of the field under study [14].

- **Splines.** These interpolators consist of a number of sections, and each fits to a small number of points so that each of the sections join up at points referred to as break points. We have analyzed the most common splines: bilinear and bicubic.

- **Weighted Moving Average.** This technique, exemplified by Inverse Distance Weighting (IDW), estimates data value for a point by calculating an inverse-distance based weighted average of the points within a search radius.

- **Thiessen Polygons (THI)** build polygons around each sample point; all points within a polygon are assumed to have the same data values as the sample point in the middle.

- **LOESS Surfaces.** LOcally wEighted Scatter plot Smooth (LOESS) performs two steps for each data point: (1) computes the regression weights for each data point in the so-called *span*, where the span controls the size of the neighborhood; (2) a weighted linear least squares regression is then performed with a second order polynomial.

- **Trend Surfaces.** A Trend Surface (TR-SRF) is basically a 3D, linear or higher order, regression surface.

- **Classification.** In Classification (CLSF), the key idea is to infer the values of one variable attribute based upon the knowledge of the values of another attribute. The basic assumption is that the value of the variable of interest is strongly influenced by another variable that can be used to classify the study area into zones.

2.2 Related Work

There are several studies that have used Kriging for coverage prediction in wireless networks. In [15], Konak estimates path loss in wireless LANs using Ordinary Kriging (OK) by defining the distance between two points as their Euclidean distance plus a term that represents the set of obstacles between the points. In [3], Phillips et al. use OK on a 2.5 GHz WiMax network setting, finding it to produce radio environment maps that are more accurate and informative than both explicitly tuned path loss models and basic fitting approaches.

In [16] and [17] Kolyaie et al. use drive testing to collect signal strength measurements, and compare the performance of empirical models and spatial interpolation techniques. Specifically, they use the Okumura-Hata empirical model, a common model used for cellular system planning and management. They evaluated its accuracy in comparison with IDW and two Kriging variants: Ordinary Kriging (OK) and Universal Kriging (UK). Though Okumura-Hata empirical model was seen to yield better results than IDW, OK and UK provided best prediction results. Our work is in a similar spirit with one crucial difference: we focus on the issues that arise when dealing with measurements obtained via crowdsourcing whereas Kolyaie et al. employed drive testing as the measurement approach.

In [4], Sayrac et al. propose Bayesian spatial interpolation for coverage analysis in cellular networks, specifically focusing on coverage hole prediction. Kitanidis' Bayesian Kriging (BK) interpolation method is used which automatically calculates the interpolation model parameters through a process of sub-settings and simulations. The main disadvantage of this method is its high computational complexity. In [5], Braham et al. consider a variant of Kriging called Fixed Rank Kriging (FRK), which is aimed at reducing the Kriging complexity. In fact, the computational complexity of Kriging is $O(n^3)$, where n is the number of measurements. The authors in [5] argue that FRK can reduce this computational complexity while keeping an acceptable prediction error.

2.3 Data Collection and Methodology

For the purposes of this study, we rely on measurement data collected in a controlled manner using a custom Android app to obtain measurement information (GPS/network location, mobile network information, location area code, cell ID, signal strength in ASU[1]) along with exact measurement location manually inputted by the user.

Considering different scenarios that capture crowdsourced measurement characteristics, we study the accuracy with different spatial interpolation techniques including various Kriging variants (OK, UK, BK and FRK) and other techniques outlined above.

To quantify accuracy of different interpolation schemes, we consider two standard metrics: Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) values (in ASU). We considered two different testing methods: leave-one-out-cross-validation (LOOCV) and calibration-and-validation (C&V); in the latter case, two-thirds of measurements are used to make a prediction in the remaining one-third. Unless otherwise mentioned, we report results for MAPE using the C&V method; other combinations yield similar results and are omitted for the sake of brevity.

In using Kriging methods, we have examined the appropriate semivariogram model to use, model parameters, etc. Here we report on this investigation for basic and common form of Kriging called Ordinary Kriging (OK). For the purposes of this specific investigation, we collected 100 signal strength measurements each in three different environments: a friendly, an urban, and an indoor environment. We assume that an environment is *friendly* if the signal propagation is not very challenged having few physical obstacles (e.g., parks and rural areas). An environment is *urban* if the signal propagation is more challenged, due to the existence of buildings and other obstacles (e.g., built environments of cities). Note that both *friendly* and *urban* are outdoor. As for *indoor* environments, the signal propagation is highly challenged by walls and other obstacles between the base station and the user equipment.

[1]ASU stands for arbitrary strength unit. Signal strength in ASU is on an integer scale and is linearly related to signal strength in dBm.

	Friendly	Urban	Indoor
Sill	32	25	30
Nugget	8	6	8
Range	250 m	120 m	80 m

Table 1: Approximate variogram model parameters in the three environments.

First, we briefly comment on the various underlying aspects of OK (semivariogram model, isotropy vs. anisotropy, model parameters); results omitted due to space limitations. While deciding about an appropriate empirical variogram model we found that exponential model followed by pentaspherical leads to lower prediction error in all the environments; consistent with results shown in other works in the literature, such as [16]. Signal propagation in cellular networks is an anisotropic phenomenon for several reasons (e.g. antenna geometries, cell sectors, etc.). However we found that Kriging works better with an isotropic model. We believe that this might be because several overlapping anisotropic phenomena together appear as an almost isotropic phenomenon.

Lastly, we notice that model parameters are actually influenced by the kind of environment. Table 1 shows the approximate variogram parameters in the three environments. Sill and nugget values are similar, where as the ranges are very different. The friendly environment has the largest range. It means that signal strength values show a remarkable correlation even if they are further away than in an urban environment, where buildings obstruct signal propagation. In an indoor environment, the signal propagation is even more challenged, so it is unlikely that far away points are still correlated.

3. IMPACT OF LOCATION INACCURACY

Crowdsourcing based measurement exploits data obtained via commodity smartphones and the built-in mechanisms to obtain the device location. However localization mechanisms are imperfect and can result in highly inaccurate locations in some cases. Therefore, a signal strength value estimated to be taken at location $s1$, might have actually been observed at $s2$, where $dist(s1, s2)$ may be greater than a certain tolerance threshold. This can clearly lead to misprediction problems. In this section we look into this problem, focusing on the outdoor urban environment and the commonly used mechanism in smartphones for outdoor localization relying on GPS.

To assess the effect of GPS inaccuracies on the accuracy with different spatial interpolation techniques, we took a total of 75 measurements of signal strength values within a small area in the city of Edinburgh; for each measurement, we stored both the actual and location reported by the phone GPS. We find that in our measurements the difference between GPS and actual locations were, on average, of 18 me-

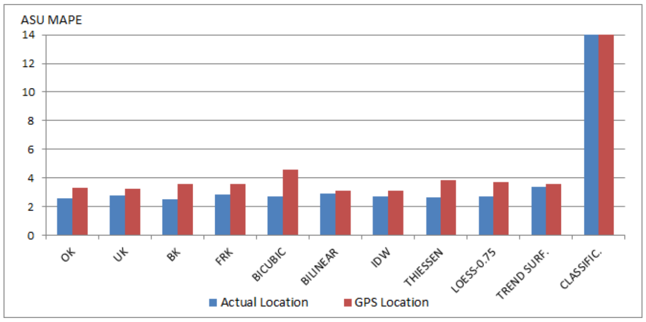

Figure 2: Impact of location inaccuracy on MAPE performance of different spatial interpolation techniques.

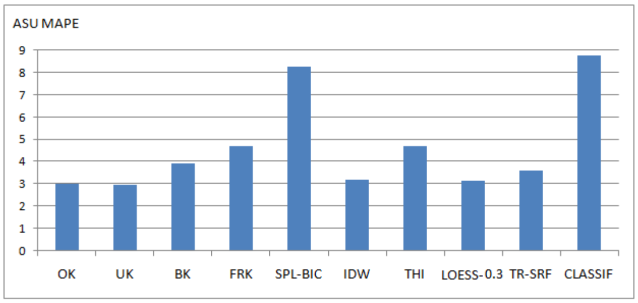

Figure 3: Prediction errors in terms of MAPE with different interpolation schemes for uniform spatial distribution of measurements.

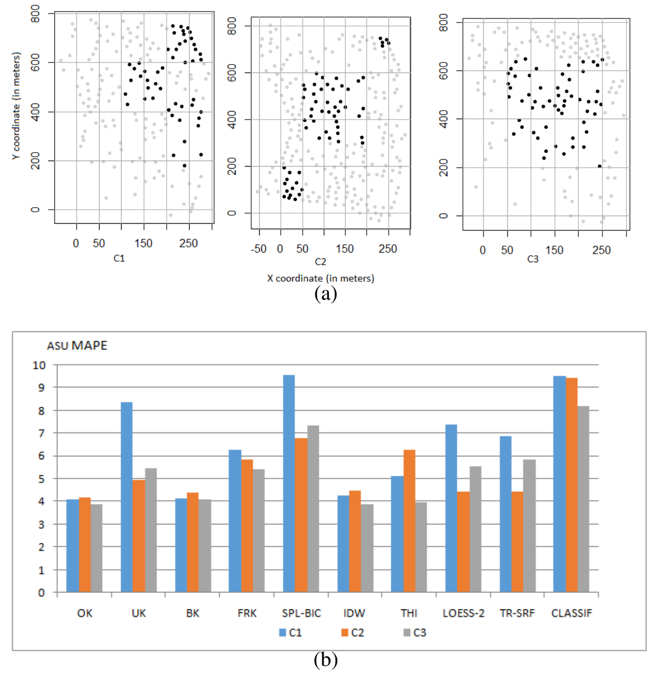

Figure 4: (a) Clustered measurement scenarios; (b) Prediction errors in terms of MAPE in each of the clustered measurement scenarios.

ters. We evaluated the accuracy of the prediction with GPS based location and actual location. Figure 2 displays the prediction errors in terms of MAPE with different interpolation techniques with $Actual$ as well as GPS based locations. We see that some techniques are more affected than others. Splines-Bicubic, Thiessen Polygons and LOESS regressions are negatively impacted. For LOESS, we only show the result with the span value that yields the best prediction — results with other span values are similar to that with Bicubic. This is no surprise, since they strongly rely on the notion of neighboring points to make a prediction. As for Kriging-based techniques, OK and UK yield better predictions even in presence of location inaccuracies while BK and FRK can be seen to be more sensitive to location inaccuracy. As per other techniques, IDW and Trend surfaces are also only slightly affected; this is as expected since they mainly rely on regional trends.

4. SPATIAL DISTRIBUTION OF MEASUREMENTS

With crowdsourcing based measurement, the spatial distribution of participant devices may not be uniform in the region of interest. In this section, we consider such scenarios with measurements distributed non-uniformly in space. To serve as a reference, we first consider a more ideal scenario with uniformly distributed measurements in space; here the goal of spatial interpolation techniques is to estimate the data in the gaps which are unmeasured.

4.1 Uniform Distributed Measurements

To assess properties and performance of spatial interpolation techniques when measurements are uniformly distributed, we use C&V approach as before but in such a way that both calibration and validation points are chosen randomly and $uniformly$ throughout the interest area. Specifically, we consider a urban outdoor open space in a park and use 479 measurements in total of which 420 measurements were used for calibration and rest for validation. The prediction error results are shown in Figure 3. The differences several of the schemes are somewhat negligible in this scenario. Exceptions to this conclusion are Splines and Classification, which perform very poorly. Like before, a few of the schemes like BK, FRK and Thiessen Polygons yield predictions with higher errors but not as high as Splines and Classification.

4.2 Non-Uniformly Distributed Measurements

We now consider the more realistic case of non-uniformly distributed measurements in space. We use measurements from the same park environment but taken in a spatially non-uniform manner, specifically to reflect *clustered measurements* and *measurements with holes*.

4.2.1 Clusters

Clustered scenarios are shown in Figure 4 (a), with black dots showing positions of calibration data and gray dots indicating validation points; the number of calibration points

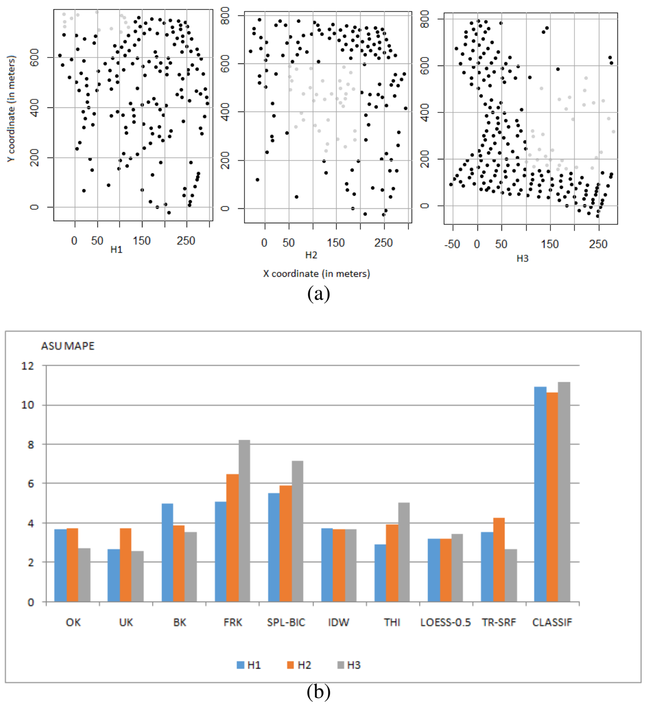

Figure 5: (a) Scenarios with measurement holes; (b) Prediction errors in terms of MAPE in each of the measurement hole scenarios.

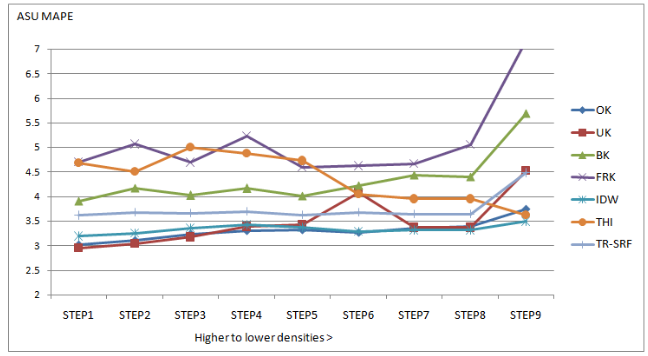

Figure 6: Impact of measurement density on MAPE values for Kriging techniques, IDW, THI and TR-SRF.

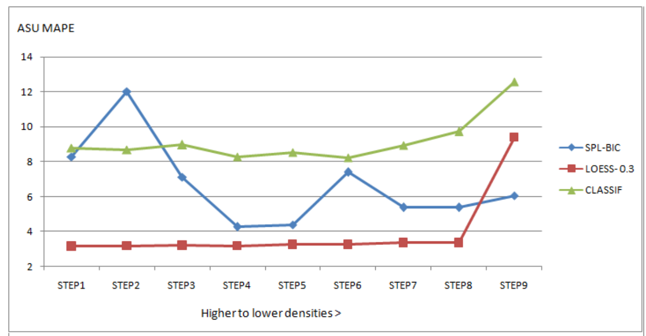

Figure 7: Impact of measurement density on MAPE values for LOESS Surfaces, Classification and Bicubic Splines.

is around 50 in all three scenarios and there are at least 100 validation points in each of the scenarios.

We find that prediction errors are widely different for different span values with LOESS. Though not shown in Figure 4 (b), LOESS with span values less than 0.75 yield quite erroneous results. As per the other schemes, we see that OK and IDW in particular consistently give lower prediction errors across all scenarios, whereas other schemes like Splines-Bicubic and Classification give worse results as before.

4.2.2 *Holes*

Scenarios with measurement holes are shown in Figure 5 (a) with black dots indicating calibration points and rest are validation points where predicted values are compared with actual values to compute the errors and MAPE. As with clustered scenarios, here we consider scenarios with different forms of holes: a smaller corner hole, a large middle hole and a bigger side hole surrounded from three sides. Prediction errors in each of these scenarios is shown in Figure 5 (b). As with clustered scenarios, the nature of the holes influences the prediction errors with different schemes. We also note that prediction errors are higher in clustered and hole scenarios compared to the initial case with spatial uniform measurements.

5. MEASUREMENT DENSITY

In this section we want to assess the impact of measurement density on the prediction. For analysis we collected about 500 measurements in a park in Edinburgh and then selected 479 measurements out of these so as to have similar density throughout the area. We used 59/479 measurements as validation dataset and the remaining 420/479 as initial calibration dataset. The size of the calibration dataset is then gradually decreased in steps to obtain different density values. We consider 9 steps. In the initial one (step 1), we have about 14 measurements per squared hectare. In the last (step 9), we have only about one.

We show the prediction error results with varying density in two graphs. Figure 6 focuses on Kriging techniques, IDW and Thiessen Polygones and trend surfaces, whereas results with LOESS, Splines and Classification are shown in Figure 7. We observe that for most of the schemes, prediction error increases as measurement density decreases as one would expect. Some of the poorly performing schemes from earlier sections like Classification, Splines, FRK and BK still yield poor results largely regardless of measurement density. Prediction error gets really worse for low measurement densities with some of the schemes (e.g., LOESS, FRK). Though not shown in Figure 7 to avoid clutter, higher span values with LOESS (e.g., span value of 2) are more robust at low measurement densities but come with somewhat higher prediction errors at higher measurement densities; the opposite holds for lower span values – we show the result with lowest span value of 0.3. Overall, we find OK and IDW to be most robust schemes across all measurement densities.

6. CONCLUSIONS

In this paper, we have experimentally studied spatial interpolation based cellular coverage prediction in the context of crowdsourced measurements. The crowdsourced measurement approach is cost effective compared to the traditional drive testing but comes with certain characteristics that introduce noise or make coverage prediction harder. Using controlled measurements taken using commodity smartphones in an urban environment, we have evaluated the accuracy of different spatial interpolation techniques, including various forms of Kriging, in several scenarios capturing unique characteristics of crowdsourced measurements. Our results show that basic form of Kriging called Ordinary Kriging generally performs well even when measurements are spatially non-uniformly distributed and when the measurement density is very low.

A possible aspect for future work is to develop a holistic framework that automatically selects the best prediction technique based on the measurement distribution, environmental information, measurement density, etc. Though we assumed a uniform random collection of measurements, we believe that improved results can be obtained by determining an appropriate initial sampling pattern according to the region under study as proposed by Zio et al. [18] for environmental surveys. A suitable initial sampling design with a representative sampling size can minimize burden on the users and the systems for drawing and manipulating crowdsourced measurements. Finally, better results can be achieved by designing an optimal second-phase sampling scheme for further minimization of prediction errors.

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