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ANALYSIS AND SIMULATION OF WIRELESS SIGNAL PROPAGATION APPLYING GEOSTATISTICAL INTERPOLATION TECHNIQUES

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ABSTRACT: This paper is a part of an ongoing research to examine the capability of geostatistical analysis for mobile networks coverage prediction, simulation and tuning. Mobile network coverage predictions are used to find network coverage gaps and areas with poor serviceability. They are essential data for engineering and management in order to make better decision regarding rollout, planning and optimisation of mobile networks.The objective of this research is to evaluate different interpolation techniques in coverage prediction. In method presented here, raw data collected from drive testing a sample of roads in study area is analysed and various continuous surfaces are created using different interpolation methods. Two general interpolation methods are used in this paper with different variables; first, Inverse Distance Weighting (IDW) with various powers and number of neighbours and second, ordinary kriging with Gaussian, spherical, circular and exponential semi-variogram models with different number of neighbours. For the result comparison, we have used check points coming from the same drive test data. Prediction values for check points are extracted from each surface and the differences with actual value are computed.The output of this research helps finding an optimised and accurate model for coverage prediction.

1. INTRODUCTION

1.1 Necessity of Radio Propagation Prediction for Mobile Network Operators

In any mobile network operator, radio propagation prediction is mainly used to demonstrate the mobile signals scatter pattern in the environment and intensity of the signals. Prediction of radio frequency in the covered area, highly assist in network planning and optimisation tasks as well as management decisions in rollout process of mobile operator. The more accurate the model for predicting radio propagation is, the easier and more profitable decision making would be. It is essential that propagation models used in computerised prediction systems be calibrated and validated using measured data. To meet this requirement there is a common activity called drive test. The drive test technique consists of using a motor vehicle containing mobile radio network air interface measurement equipment that can detect and record a wide variety of the physical and virtual parameters of mobile cellular service in a given geographical area.

Path loss which is attenuation in power density of the signal in wireless communication is influenced by many effects like free-space loss, refraction and absorption. At the same time different environmental, geographical and terrain variables also affect the signal propagation. As a result, geostatistical methods which describe continuity of spatial/temporal data variables can provide a successful experiment in finding accurate propagation models.

1.2 Study Area

The study area is Khorram-Abad the principal city of Lorestan, a province in west of Iran. This city has been chosen as study area for its special terrain characteristics. It is located in the Zagros Mountains which are the largest mountain range in Iran and Iraq. By choosing a mountainous city instead of a flat one, it was possible to find the most accurate propagation prediction model. In Figure 1, location of the city and its topography can be seen.

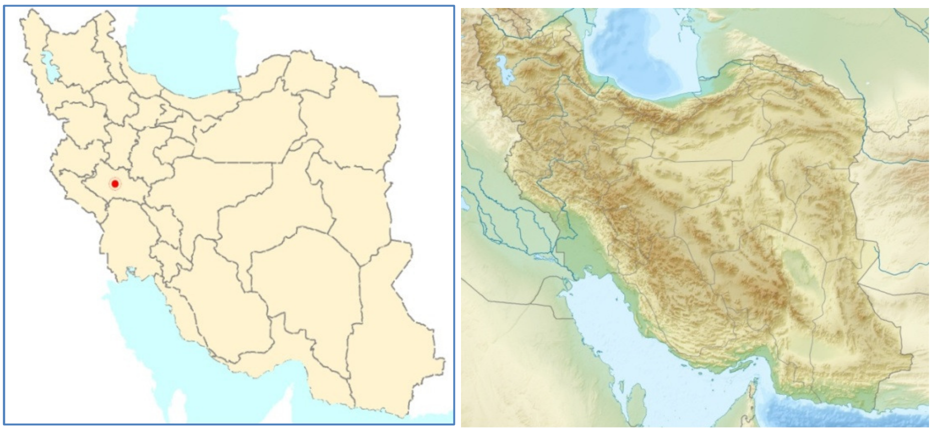

Fig. 1 Khorram-abad location and topography

1.3 Paper Structure

In section 2 of this paper a summary of kriging components which have been used in this study are presented. In section 3 the method used is described in detail and results are discussed in section 4.

2.1 Geostatistics Overview

Geostatistics has been used since early 1950's in mining engineering field and this theoretical framework has been successfully applied in other type of spatial problems over the last decades (Matheron 1963).
As mentioned, path loss data is highly affected by spatial parameters, therefore geostatistics has high potential to be used in sampling and prediction of this data. Kriging, as a geostatistical interpolation technique, is a flexible algorithm.There are different types of kriging which could be used for interpolation such as ordinary kriging, universal kriging, and indicator kriging. Semi-variogram is the basic component of kriging which depicts the spatial autocorrelation of the measured sample points and employs spatially distribution of data in interpolation. There are different models which are used as template for

semivariogram such as spherical, gaussian, circular and exponential (Sullivan & Unwin, 2002).

2.1.1 Semivariogram

The variogram characterises the spatial continuity or roughness of a data set. Usually one dimensional statistics for two data sets may be nearly identical, but the spatial continuity may be quite different. The difference between variogram and semivariogram is simply a factor of 2. The variogram was originally defined as below (Equation 1): (Barnes, R. 2003)

$$2\gamma(\Delta x, \Delta y) = \varepsilon[\{Z(x+\Delta x, y+\Delta y) - Z(x,y)\}^2] \tag{1}$$

where:
Z(x,y): is the value of the variable of interest at location (x, y)
ε[] : is the statistical expectation operator

In Equation 1, 2γ( ) was given the name variogram. The function of practical interest was γ( ) given the name semi-variogram. Since only the function γ( ) is used in kriging, the prefix semi- is regularly dropped, and the function γ( ) is interchangeably called the variogram and the semi-variogram in the geostatistical literature (Barnes, R. 2003).

According to (Cressie 1993, Chiles and Delfiner 1999, Wackernagel 2003) the theoretical variogram should be the empirical variogram which is used as the first estimation of variogram for spatial interpolation by kriging.

The empirical variogram γ(h) is defined as Equation 2 for observations z_i , $i=1,\dots,k$ at locations $x_1,\dots, x_k$ (Cressie 1993):

$$\hat{\gamma}(h) = \frac{1}{|N(h)|}\sum_{(i,j)\in N(h)}|z_i - z_j|^2 \tag{2}$$

where:
N(h): set of pairs of observations i, j
h= |xi − xj|: lag
|N(h)|: the number of pairs in the set

However, the empirical variogram cannot be computed at every lag distance *h,* and it is not ensured it is a valid variogram required by kriging method. In applied geostatistics the empirical variograms are thus often approximated by model function ensuring validity (Chiles & Delfiner 1999). Some important models are:

Gaussian Semivariogram Model (Equation 3) (Wackernagel, 2003)

$$\gamma(h) = b\left(1 - e^{\left(-\frac{|h|^2}{a}\right)}\right)\ and\ a,b > 0 \tag{3}$$

Spherical Semivariogram Model (Equation 4) (Armstrong, 1998)

$$\gamma(h) = \begin{cases} C\left(\frac{3}{2}\frac{|h|}{a} - \frac{1}{2}\left(\frac{|h|^3}{a^3}\right)\right) & |h| < a \\ C & |h| \geq a \end{cases} \tag{4}$$

Circular Semivariogram Model (Equation 5) (Haining, 1993)

$$\gamma(h) = \begin{cases} c_0 + c\left(1 - \left(\frac{2}{\pi}\right) arccos\left(\frac{h}{a}\right) + \left(\frac{2h}{\pi a}\right)\left(1 - \left(\frac{h^2}{a^2}\right)\right)^{\frac{1}{2}}\right) & 0 < h \leq a \\ c_0 + c & h > a \\ 0 & h = 0 \end{cases} \tag{5}$$

Exponential Semivariogram Model (Equation 6) (Armstrong, 1998)

$$\gamma(h) = C\left(1 - e^{\left(-\frac{|h|}{a}\right)}\right) \tag{6}$$

2.1.2 Universal Kriging

Universal kriging is a form of interpolation that takes into account the local trends in data when minimising the error associated with estimation. The presence of such trends, or drifts as they are known, is identified qualitatively, and their form found quantitatively by structural analysis, which simultaneously estimates semi-variances of the differences between the drift and actual data. The resulting semi-variograms are then used for the interpolation (Wackernagel, 2003).

Universal kriging assumes the model where μ(s) is a deterministic function (Equation 7).

$$Z(\mathbf{s}) = \mu(\mathbf{s}) + \varepsilon(\mathbf{s}) \tag{7}$$

2.2 Review of Previous Researches

Geostatistical techniques offer interpolation methods for describing the continuity of spatially/temporarily variable data which is essential feature of many natural phenomena. Over the last decades, this theoretical framework has been successfully applied in other types of spatial problems (Konak, 2010). As it is mentioned above, signal path loss is highly influenced by spatial parameters, therefore geostatistics has high potential to be implemented for such purpose (Arpee J. et al., 2000).

There are few researches conducted using geostatistical techniques for modelling wireless propagation models. In a recent paper, Konak (2009) reports that ordinary kriging is competitive with radial basis ANNs to estimate the signal-to-noise ratio in cellular wireless networks. Konak in 2010 extends the ordinary kriging approach proposed in 2009 by considering path loss due to obstacles and other factors in indoor environments.

3. METHOD

The objective of this research is to evaluate different interpolation techniques in coverage prediction based on drive test data and compared using check points. Following, our method is presented:

3.1 Data Preparation

We analysed raw data collected by drive testing a sample of roads in the study area (Figure 2). First this data was processed to eliminate gross errors. Totally, 58,029 points were collected.

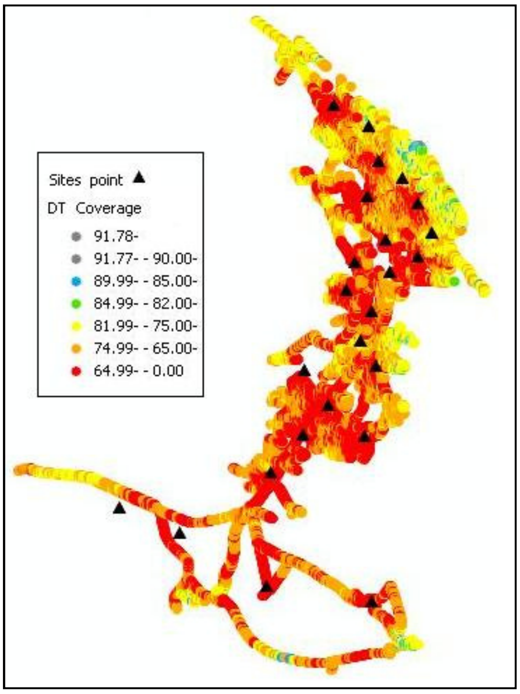

Fig. 2 Drive test of roads in the study area measurements are in dBm

3.1.1 Check Points Selection

To compare the interpolation methods for this study, we selected 15,417 points as check points and other 42,612 points were used for prediction. Although kriging could be evaluated by error prediction analysis which is one of the advantages of this technique, we used check points to be able to compare the result of this technique with other interpolation techniques. Check points were selected by creating a grid network to ensure they are distributed evenly (Figure 3).

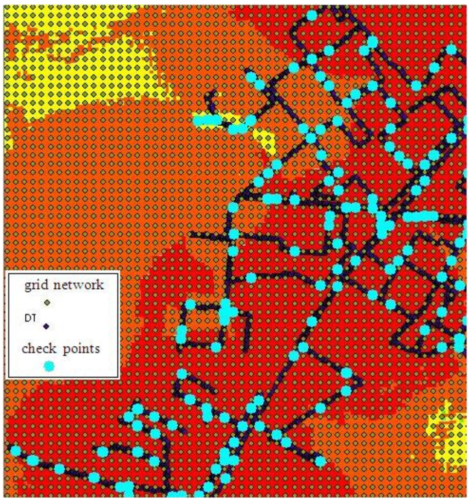

Fig. 3 Selection of Check Points by a Grid Network

3.2 Continuous Surface Creation

After data preparation, surfaces using interpolation methods described in section 2 are created. The methods used are Inverse Distance Weighting (IDW) with different power and number of neighbours and universal kriging with gaussian, spherical, circular and exponential models for semivariogram with different number of neighbours. Two of the created surfaces are depicted in Figure 4 (Universal Kriging, Circular variogram) and Figure 5 (IDW, 3rd Power).

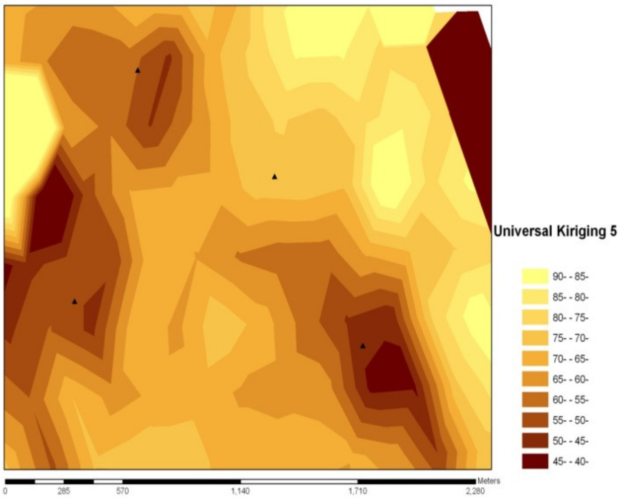

Fig. 4 Surface created by Universal Kriging having Circular Semivariogram

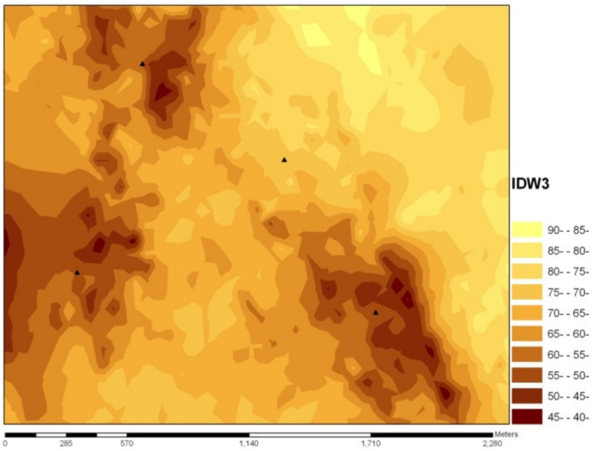

Fig. 5 Surface created by IDW method, having 3rd power and 50 neighbour

In next section, the best fit output of each method is presented:

3.2.1 IDW

IDW surfaces with different number of neighbours (10, 30, 50, 100, and 1000) and powers (2, 3, 4, 5) were fitted to measured data. The results show that power 3 with 50 neighbours is best fitted considering the precision and computational time. Summary of some of tested combinations are in Table 1:

Tab. 1 Overview of IDW surfaces

S3	idw_6	Power4-NoNei:50	4.85165
S1	idw_2	Power3-NoNei:50	4.697553
S2	idw_3	Power3-NoNei:1000	4.684434

3.2.2 Universal Kriging

Among the surfaces created by universal kriging interpolation techniques, specifications of below four surfaces (Table 2) are shown in details in following tables:

Tab. 2 Selected surface created by universal kriging

S6	Univ_Kriging3	Gaussian
S4	Univ_Kriging5	Circular
S7	Univ_Kriging2	Spherical
S5	Univ_Kriging4	Exponential

Tab. 3 Gaussian Semi-variogram Model

Method: Universal Kriging_3	
Trend type	Third
Neighbors to include	30
Include at least	10
-Trend removal	Local Polynomial Interpolation
-Model type	Gaussian

Tab. 4 Spherical Semi-variogram Model

Method: Universal Kriging_2	
Trend type	Third
Neighbors to include	30
Include at least	10
-Trend removal	Local Polynomial Interpolation
-Model type	Spherical

Tab. 5 Circular Semivariogram Model

Method: Universal Kriging_5	
Trend type	Third
Neighbors to include	30
Include at least	10
-Trend removal	Local Polynomial Interpolation
-Model type	Circular

Tab. 6 Exponential Semivariogram Model

Method: Universal Kriging_4	
Trend type	Third
Neighbors to include	30
Include at least	10
-Trend removal	Local Polynomial Interpolation
-Model type	Exponential

3.3 Comparison

For the result comparison, we used check points. Prediction values for check points are extracted from each surface and the difference with actual value are computed. The root mean square is used to compare the methods. (Table 7)

Tab. 7 Surfaces Comparison

Surface	Model	Detail	Sigma
S2	idw_3	Power3	4.6844335
S6	Univ_Kriging3	Gaussian	4.0973997
S4	Univ_Kriging5	Circular	3.7062182
S7	Univ_Kriging2	Spherical	3.6686279
S5	Univ_Kriging4	Exponential	3.3519531

4. RESULT

The outlines of results for this study are listed below:

- All Kriging methods used here are 30% more accurate in average than IDW and have acceptable error.
- for IDW method, power 3 surface is the best fit for modeling coverage prediction .
- Surfaces created by Universal kriging demonstrate:
    - Exponential model for semi-variogram is the best fit for coverage prediction among other assessed ones.
    - Results show the suitability of exponential and spherical semi-variograms are almost equal and placed after exponential model. The least accurate model in this regard is Gaussian model.
- In all tested types of interpolation:
    - The higher the number of neighbors is, the more accurate the results will be.
    - However, an optimal number of neighbors can be found, beyond which the computational time would be a cost to reach more accuracy.

The output of this research helps in finding an optimised and accurate model for mobile networks coverage prediction. Mobile network coverage predictions are used to find network coverage gaps and areas with poor serviceability. They are essential data for engineering and management in order to make better decision regarding rollout, planning and optimisation of mobile networks.

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