Prediction of wireless network connectivity using a Taylor Kriging approach

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Abstract: The research aim of this paper is to investigate the effectiveness of a new Kriging model which uses Taylor expansion to predict wireless network connectivity. Wireless network connectivity is measured by the strength of emitted signal power from the tower to the point in question. The prediction results are compared with those from the literature where an Ordinary Kriging model and a neural network are used to conduct the same prediction. Root mean squared error (RMSE) and maximum absolute relative error (MARE) show that the prediction results of the new Kriging model are much better than those obtained before with average differences from 51.56% to 85%. This study shows the promise of the new Kriging model to accurately estimate wireless signal strength.

Keywords: Taylor Kriging; prediction modelling; wireless network connectivity.

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1 Introduction

Wireless network research deals with all types of connections without cables. Network connectivity is defined as the ability to connect to a network connection point with some minimum threshold of signal strength and quality that allows ongoing communication (Nasereddin et al., 2005).

The signal to noise ratio is a measure of network quality and it is a ratio of desired signal to undesired signal (noise) in the average level of transmission. The distance of a point in a network to the transmitting tower serving the point and the maximum value of transmitted power are used to calculate the signal to noise ratio in this paper.

This paper uses a new Kriging model based on Taylor expansion (Liu, 2009) to predict the signal to noise ratio, that is, the quality of connectivity, for wireless networks. The goal is to explore a more effective method for the connectivity prediction of wireless network. The rest of this paper is organised as follows. The second section reviews the applications of Kriging especially in wave propagation prediction. The third section introduces the Kriging approach. The fourth section presents the empirical analysis and compares the prediction results. Finally, the conclusions and future research directions are provided.

2 Literature review

Kriging was originated in geostatistics and revolutionised that field (Matheron, 1963; Kumar, 2007; Oliver and Gotway, 2005). Several empirical studies proved its superiority over other interpolating techniques such as splines (Laslett, 1994). Kriging has been used in many fields including cost estimation (Chaveesuk and Smith, 2005; Baioumy et al., 2008), simulation interpolation (Barton, 1994; Kleijnen and van Beers, 2005), and optimisation (Huang et al., 2006; Liu and Smith, 2007). Recently, Kriging has been applied to the prediction of wave propagation in space due to its accuracy advantage in performing the spatial interpolation. De Doncker et al. (2002) and De Doncker et al. (2003) adopted Kriging to predict electromagnetic wave propagation. Leflbvre et al. (1996) indicated that Kriging appears to be a useful approach for many applications in electromagnetics, particularly when computational time is an important issue. For geosensor networks, energy efficiency, nodes localisation and data routing are the critical problems. Reis (2005) used Kriging to solve the selection problem of locations in the geosensor deployment. Yu et al. (2006) made the first attempt to quantify the sensitivity of data processing algorithms in sensor networks to data using Kriging as one of the considered algorithms. This reference identified a unique feature of the synthetic data generation framework and thus made both synthetic data generation and evaluation scalable. When some points of a wireless sensor network (WSN) are covered by more than a given number of sensors, it is possible to instruct the surplus sensors to enter a low power sleep mode in order to conserve the energy of the network while maintaining the required coverage level. Tynan et al. (2005) demonstrated the effectiveness of using Kriging interpolation to identify redundant sensors.

Li et al. (2005) utilised Kriging to generate the error correction map of non-line-of-sight (NLOS) signal propagation for network-based mobile positioning. The NLOS error systematically increases the positioning error. A NLOS error correction map is generated by Kriging to mitigate the effect of NLOS error and rectify the distorted mobile station location. Li et al. (2006) described several innovative implementations of wireless LAN (WLAN) positioning systems developed by researchers at the University of New South Wales (UNSW) and presented the detailed experimental results of the research. The reference indicated that Kriging is one effective method and it is competitive in terms of accuracy.

Bartolacci et al. (2004) suggested a connectivity decision support system (CDSS) framework for wireless networks that would provide location-based information to users. The reference claimed that the proposed CDSS framework can increase the 'connectivity' of users and thus result in a decreased number of dropped or poor quality calls. The applicability of the CDSS framework includes cellular networks, ad hoc networks, and wireless IEEE 802.11-based networks. By using a neural network (NN) approach, Nasereddin et al. (2005) proposed a CDSS based on generated connectivity maps. The paper used the signal strength data from active wireless users to train an NN and then predict the signal strengths or coverage for the locations where no active user is reporting. The prediction results are used to generate a coverage map. Konak (2009) introduced Kriging as a new tool to predict the network coverage in wireless networks. The proposed approach aims to reduce the cost of active site surveys by estimating network coverage at points where no site survey data is available. This approach is compared with a radial basis function artificial NN using several problems. Following the work of Nasereddin et al. (2005), Bartolacci et al. (2004) and Konak (2009), this paper uses a Kriging model based on Taylor expansion to predict the quality of connectivity for wireless networks of 14-towers, 27-towers, and 45-towers. The prediction results from the new Kriging model are compared with those of the references.

3 Kriging approach

Kriging is a geostatistical interpolation technique similar to inverse-distance weighted average (IDWA) which estimates the elevations at the reference points. That is, Kriging uses the combination of weights at known points to estimate the value at an unknown point. It fits a mathematical function to a specified number of points, or all points within a specified radius, to determine the output value for each location.

Kriging assumes that the variable $Z(\boldsymbol{X})$ can be written as the sum of a deterministic component $\mu(\boldsymbol{X})$ and a stochastic component $R(\boldsymbol{X})$ (Kumar, 2007):

$$Z(\boldsymbol{X}) = \mu(\boldsymbol{X}) + R(\boldsymbol{X}) \tag{1}$$

The deterministic component $\mu(\boldsymbol{X})$ is the expected value of the regionalised variable $Z(\boldsymbol{X})$ at location $\boldsymbol{X}$ which is a vector. A fundamental assumption of Kriging is that the covariance between any two locations depends only on the distance between the two locations and can be expressed as a function of the distance. In Simple Kriging, it is assumed that the mean $\mu(\boldsymbol{X})$ is zero across the field of interest. Ordinary Kriging is the most commonly used type of Kriging. It assumes that $\mu(\boldsymbol{X})$ is an unknown non-zero constant. In the third type of Kriging, Universal Kriging, the mean is assumed to have a functional dependence on spatial locations and can be approximated by a chosen model with the form below (Liu, 2009):

$$\mu(\boldsymbol{X}) = \sum_{\mathrm{j=1}}^{\mathrm{k}} a_j f_j(\boldsymbol{X}) \tag{2}$$

where a_j is the jth coefficient to be estimated from the data, $f_j(\boldsymbol{X})$ is the jth base function of spatial coordinates that describes the drift of the mean, and k is the number of base functions. The Kriging estimator is given by a linear combination:

$$\hat{Z}(\boldsymbol{X}) = \sum_{i=1}^{n} \lambda_i Z\left(\boldsymbol{X}_i\right) \tag{3}$$

Weights λ_i, $i = 1, \ldots, n$ are chosen to satisfy the following statistical condition:

$$E\left[\hat{Z}(\boldsymbol{X}) - Z(\boldsymbol{X})\right] = 0 \tag{4}$$

$$Var\left[\hat{Z}(\boldsymbol{X}) - Z(\boldsymbol{X})\right] \text{ is minimised} \tag{5}$$

The Konak estimation approach (Bartolacci et al., 2004; Konak, 2009) uses Ordinary Kriging and requires the calculation of a new Kriging model for each point to be estimated. However the Kriging used herein allows for the calculation of a single model to be used over the entire range of operation.

The Kriging model in this paper uses a Taylor expansion series to approximate $\mu(\boldsymbol{X})$ and can improve the prediction accuracy of Kriging (Liu, 2009). This model is termed Taylor Kriging. In Taylor Kriging, Taylor expansion is used to identify the base functions. Taylor expansion has very good non-linear functional approximating capabilities and thus can assist Kriging in capturing the non-linear data mean drift. In Taylor Kriging, sample standard deviation is used as the measurement unit of influence distance in the covariance function. Since different problems have different data magnitudes, sample standard deviation simplifies the parameter setting of influence distance.

4 Computational experience

The data of wireless networks with 14, 27 and 45-towers from (Nasereddin et al., 2005; Bartolacci et al., 2004; Konak, 2009) are used as the test problems. The inputs are the power of the tower serving that point (that is, the closest tower) and the Euclidean distance to the tower. The output is the log (base 10) of the signal to noise ratio. In (Konak, 2009), the inputs are the x and y coordinates of the tower and the transmitted power of the tower serving that point.

A Kriging model with the 3rd order Taylor expansion and an influence distance of two standard deviations for the covariance function is used. The prediction results from the Taylor Kriging are compared with the actual results and the prediction results of Ordinary Kriging used in Konak (2009) and called Konak Kriging in this paper and an NN also from Konak (2009).

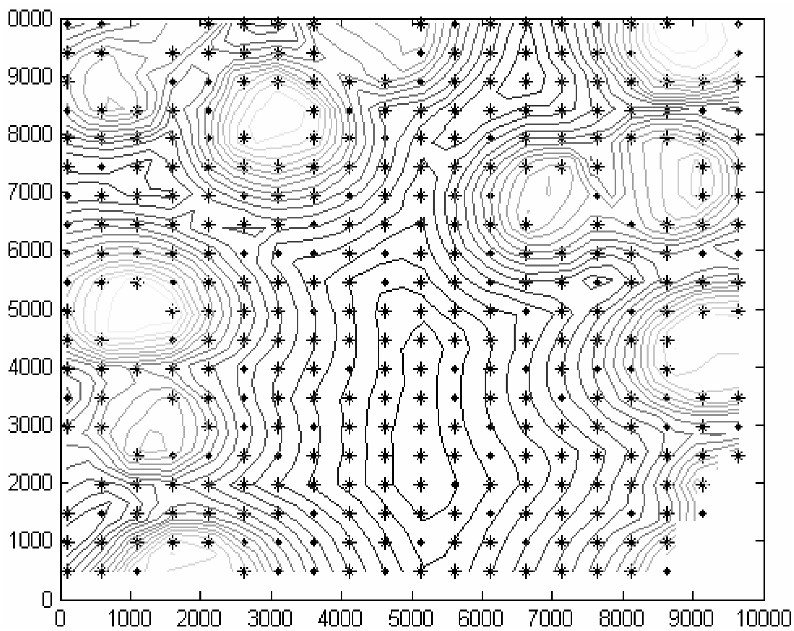
Note that the magnitudes of the input parameters (distance and power) are significantly different. To avoid the influence of differing data magnitudes on predicted values, the data is normalised. The normalisation formula is as follows:

$$x_i' = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \tag{6}$$

where $\max(x_i)$ and $\min(x_i)$ represent maximal and minimal values that x_i can take, respectively.

Three different strategies for training (that is, fitting) of the Kriging model and testing of the fitted model are considered. These are 25% training, 50% training and 75% training. The total dataset for each problem was 358, 322 and 288 points for the 14, 27 and 45-tower problems, respectively. So, the 50% training strategy for the largest problem would use 144 data points to calculate the model and 144 data points to test the model. Points were randomly selected by (Konak, 2009) and the same points as in this paper were used (see Figure 1 for an example).

Figure 1 The coverage map of the 14-tower problem and the training set for 75% training



Notes: * denotes the points where the signal-to-noise ratios are sampled and
• denotes test points.

The root mean squared error (RMSE) and the mean absolute relative error (MARE) are the performance measurement standards of prediction accuracy and their mathematical formulas are below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(y_{ai} - y_{pi}\right)^2}{n}} \tag{7}$$

$$MARE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_{ai} - y_{pi}}{y_{ai}} \right| \tag{8}$$

Table 1 Results for different numbers of training versus testing points

	25% training, 75% testing	*50% training, 50% testing*	*75% training, 25% testing*
		4-tower wireless network	
		Konak-Kriging	
RMSE	3.7	1.7	1.3
MARE	89.3	24.6	4.2
		NN	
RMSE	3.5	2.1	1.3
MARE	72.2	17.0	3.9
		Taylor Kriging	
RMSE	2.1	1.7	1.5
MARE	51.4	14.8	3.3
		27-tower wireless network	
		Konak-Kriging	
RMSE	3.4	2.7	1.4
MARE	61.0	54.0	285.0
		NN	
RMSE	3.8	3.0	2.0
MARE	357.0	50.0	379.0
		Taylor Kriging	
RMSE	2.05	2.4	1.4
MARE	11.3	40.0	99.0
		45-tower wireless network	
		Konak-Kriging	
RMSE	3.5	8.5	2.6
MARE	59.0	411.6	57.9
		NN	
RMSE	4.1	3.4	2.9
MARE	51.9	339.5	77.3
		Taylor Kriging	
RMSE	2.2	2.1	1.1
MARE	46.6	297.5	19.0

Table 1 summarises and compares the results from Taylor Kriging, Konak-Kriging and NN for the 14-tower, 27-tower, and 45-tower networks with different percentages of training and testing points. In this table, the errors from Taylor Kriging are all significantly less than the other approaches except for the shaded parts. For the maximum sized training set for the smaller problems, all methods perform comparably. However when training data is constrained or the problem is large, Taylor Kriging is much better.

Table 2 shows the average values of RMSEs and MAREs for the three types of training and testing sample sets. The average differences of MAREs between Taylor Kriking and Konak-Kriging and NN are 51.56% and 85%, respectively.

Table 2 Average errors across all problems

	25% training plan	*50% training plan*	*75% training plan*
		Konak-Kriging	
RMSE	3.5	4.3	1.8
MARE	69.8	163.0	115.7
		NN	
RMSE	3.8	2.8	2.1
MARE	160.4	135.6	153.4
		Taylor Kriging	
RMSE	2.1	2.1	1.3
MARE	36.4	117.4	40.5

Figure 2 14-tower wireless network comparison at 50% training and 50% testing

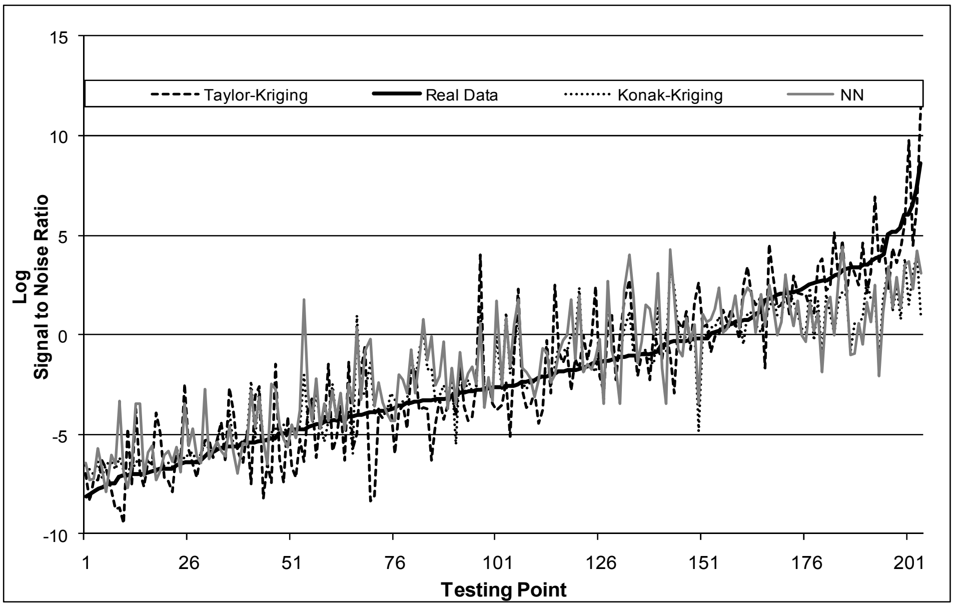


Figure 3 27-tower wireless network comparison at 50% training and 50% testing

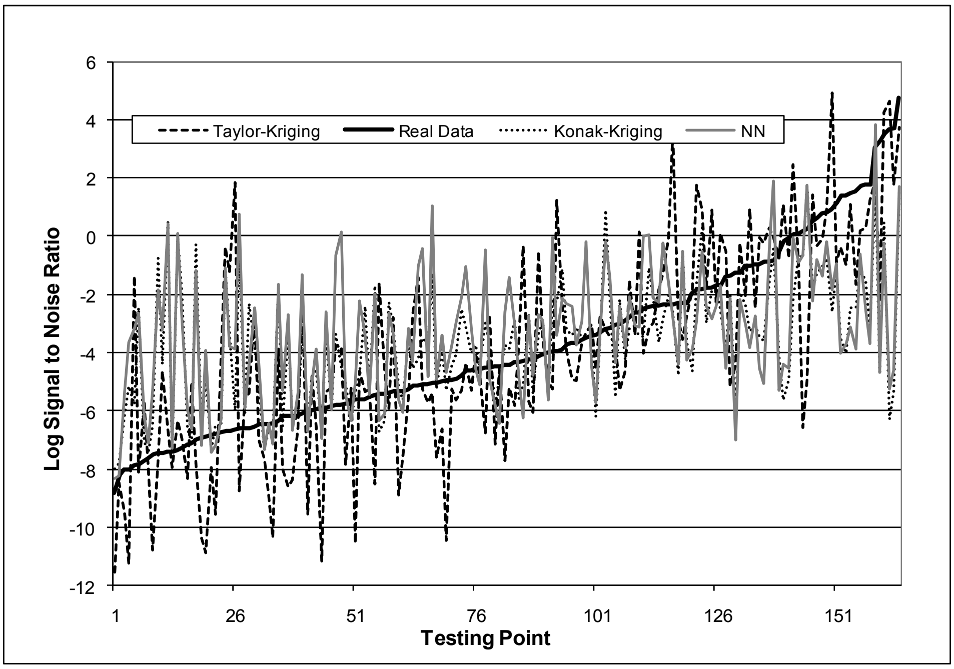
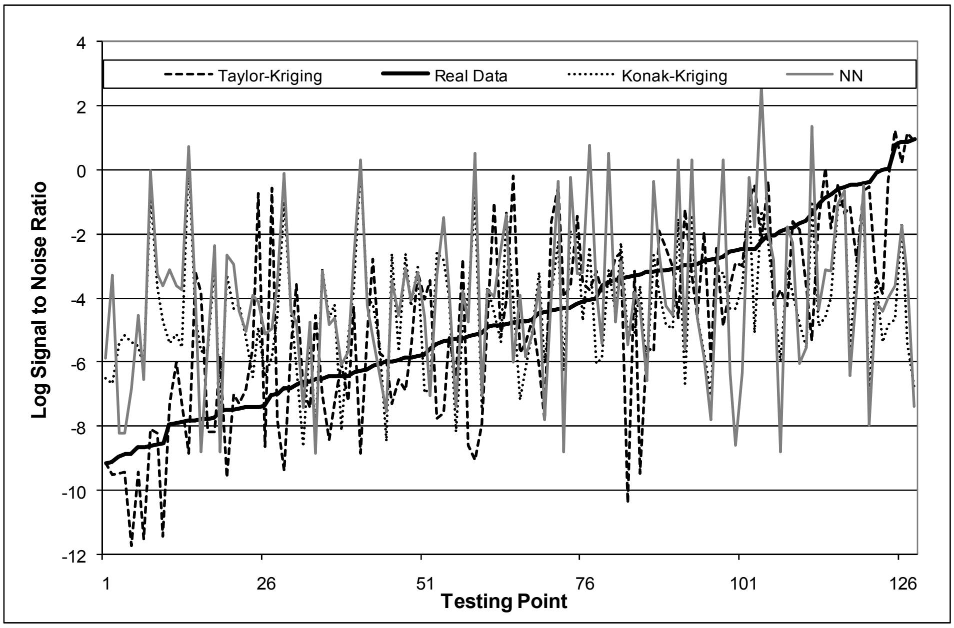


Figure 4 45-tower wireless network comparison at 50% training and 50% testing



The predicted results from the wireless networks with 50% training and testing sample sets are used as examples to diagrammatically describe the prediction performance of the different methods in Figures 2 through 4. The real data (log of signal to noise ratio) is sorted from low to high so that the figures can easily show the prediction accuracy. An entry of less than zero indicates noise greater than signal (a ratio <1). The figures show that the predictions are unbiased. Predictions for larger problems are less accurate than for smaller problems.

5 Conclusions

This paper is an expanded version of Al-Khafagi, Liu and Smith (2009). This study results show the promise of using Taylor Kriging to estimate signal strength of wireless networks using inputs of distance to tower and tower signal strength. Once fitted for a given problem (set of towers and known signal strengths at some points), the Kriging model can be used to estimate the signal strength for any point in the domain. Taylor Kriging has the advantage of prediction accuracy over Ordinary Kriging for datasets with fewer training points. However, the error of prediction can still be quite high. Future research should aim to reduce the prediction error across the domain.

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