
Yuhao Wang*, Member, IEEE, Ge Dang†, Yang Si* and Huilin Zhou*

*School of Information Engineering, Nanchang University, China, 330031
Email: Yuhao.wang@ieee.org
†China Mobile Group Guangdong Co., Ltd., China, 510100
Email: Dangge@gd.chinamobile.com

Abstract—In order to catch the iterated growth and evolution of the future mobile communications, this paper has proposed to study on a novel prediction model for radio propagation as well as its applications based on the radio propagation theory and the inverse theory. The prediction of radio propagation in a mobile network can be treated as an inverse problem. Instead of through the high-precision geometric modeling of wireless environments, this problem can be solved by an inversion of the measured data (under all priori constraints). So a complicated propagation prediction problem can be simplified to a system of large scale ill-condition equations, which can be solved by genetic algorithm appropriately. The effectiveness of the proposed method has been demonstrated using experiments under various radio environments in Guang Dong, China. It was shown that the prediction results were approximately consistent with independent checking samples. The advantages of the proposed strategies compared with existing approaches are well demonstrated.

I. INTRODUCTION

The 3rd Generation (3G) radio access network relies upon novel, more flexible and efficient communication methods, a consequence of which is that novel modeling and planning approaches become of prime importance to the networks roll-out success. The main issue in 3G network planning was capacity and coverage, which, because no real planning tools were then available, were derived either analytically or using manual measurement regimes [1]. The coverage prediction is a crucial and fundamental task in the planning of any practical radio access network, which use propagation models to calculate the desired network characteristics and decide whether the intended quality of services has been met. From a mathematical point of view, it can be solved as a forward problem or as an inverse problem[2]. As a forward problem, to predict the coverage of the appointed cell, it is usually necessary to establish a theoretical or empirical propagation model simplified to a certain extent and to combine it with some given values of the model parameters through physical analysis or experiential knowledge about the propagation environments and mechanisms. As an inverse problem, the coverage can be reconstructed by an inverse approach based on a few actually measured data and some concerned parameters.

Many theoretical and empirical propagation models were proposed by many authors to predict the coverage of radio cells [3], such as statistical models, site-specific models and semi-deterministic statistical models.

All models mentioned above take the coverage prediction as a solution to a forward problem. In this paper, we have proposed an enhanced inversion propagation prediction model for a single cell. Some early results of the inversion propagation model had been published in [4]-[5], in which the computerized tomography (CT) techniques had been used to solve the coverage predictions for multi-cells[5]. The inversion method had some potential in very low computational cost and without the help of a digital map[4]. But there are some limitations with the CT method, like the restriction to the propagation loss factor, its dependence on the orientation of the rays was ignored by using the CT method, which means that the propagation loss factor in each pixel for the rays coming from different cells was predicted in the average sense. Under this approximation, the results of the coverage prediction are inexact and maybe obviously deviate from the real distribution sometimes. In fact, the propagation loss factor includes the influences of both the path loss and shadow fading, and the latter is an irregular variable. There are almost no isotropic scatters in the actual urban environment, which implies that the propagation loss factor depends on the orientation of the rays to a great extent. The second restriction from the multi-cell prediction model based CT method is not universal, for instance, it can not applied to the scenario that the BS is inside of the predictive area.

So in this paper, we have proposed an enhanced inversion propagation model for a single cell. The kernel idea of the proposed model is to consider that the measured data contains the effects of propagation loss brought by the terrain and buildings. Therefore it is possible to predict the propagation loss between any two points along the virtual propagation path from the base-station (BS) to the mobile-station (MS) within a predicted area can be deduced in an average sense with reasonable accuracy, based on an aperture series of measurements, finite and limited in extent, taken along the periphery of this area. Consequently, this enables us to convert the coverage

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prediction of a single cell into solving a system of large scale ill-condition equations. So we used the genetic algorithm to optimize the solution of the proposed model and have got some desired results.

The paper is organized as follows. Firstly, the prediction model is proposed and the details of the solution to the model are described. Then the detail of prediction flowchart is presented in Section III. Furthermore the prediction results of the examples are evaluated by a comparison with the checking samples in Section IV. Finally, the conclusion is given in Section V.

II. THE PROPOSED MODEL AND IT’S SOLUTION

A. The Inversion Propagation Prediction Model

Here, a parameter, \( \alpha(r) \), is introduced as called the propagation loss factor that indicates the propagation loss along a unit of propagation distance,

\[
\alpha(r) = \lim_{\Delta r \to 0} \frac{\hat{P}_{Loss}(r + \Delta r) - \hat{P}_{Loss}(r)}{\Delta r} = \frac{d\hat{P}_{Loss}(r)}{dr} \tag{1}
\]

where, \( r \) and \( \hat{P}_{Loss}(r) \) are the propagation distance and the median of propagation loss in unit of decibels from the BS to the MS respectively, and the latter can be obtained after removing the fast fading from the instantaneous values of the signal powers by the spatial filtering approach.

A majority of propagation paths are not linear paths from BS to MS. A projection operator, \( R_i \), is defined to act on \( \alpha(r) \),

\[
\hat{P}_{Loss}(r) = R_i[\alpha(r)] \tag{2}
\]

Eq. (2) gives a general prediction model of propagation loss in mobile communication, which can be solved as an inverse problem.

In [7], when the BS’s antenna is located higher than the surrounding buildings and scattering objects are located uniformly within a circle around the MS, it can be described by the geometrically based single bounce model, in which each multipath component of propagation signals undergoes only one bounce traveling from the BS to the MS. Then after the multipath components are removed by the spatial filtering approach, the total propagation loss can be approximatively equivalent to that along the direct path from the BS to the MS, which is called as the virtual propagation path. Taken these considerations, the projection operator \( R_i \) can be simply replaced by a line integral. Eq. (2) is turned into

\[
\hat{P}_{Loss}(L) = \int_{L} \alpha(r) dr \tag{3}
\]

where \( L \) is the virtual propagation path.

Eq. (3) can be expressed as a set of linear equations after the predicted area has been discretized into pixels,

\[
\hat{P}_{Loss} = D\alpha + E \tag{4}
\]

where \( \alpha \) is the propagation loss factor in each pixel and \( \hat{P}_{Loss} \) indicates the total propagation loss along the virtual propagation paths within the predicted area which can be obtained by the measurements, \( D \) is a \( M \times N \) matrix determined by the geometry of the predicted area and selected virtual propagation paths; \( M \) and \( N \) are the numbers of the virtual propagation paths and the pixels, respectively, \( E \) represents an error term due to the approximate nature of the series expansion and inaccuracy in measurements.

In Eq. (4), \( \alpha \) is unknown, and some measured data are collected along the periphery of predicted area, which can construct \( \hat{P}_{Loss} \). However \( N >> M \) in the actually reconstruction, Eq. (4) is a large scale ill-condition equation. So the solution of the inversion propagation model is left to solve

\[
\min E = \min \{ D\alpha - \hat{P}_{Loss} \} \tag{5}
\]

So genetic algorithm can be applied in Eq. (5).

B. Genetic Algorithm

The GA is a nature-inspired algorithmic technique for the optimization of problems based on the principles of natural evolution. The individuals with better genes survive in the evolution process, while others are eliminated. The survivors mate with each other and bear their offspring. The offspring inherit their parents genes, which are the same as those of their parents or even better. Consequently, the best genes could be obtained by iterating the evolution process. The GA used here is a binary version and much like that in [8]. Based on the standard operations of selection, crossover and mutation, the GA can easily solve the optimization problem. According to Eq. (5), some restraint conditions as follows: 1) \( \alpha \) is positive and in \([0,10]\), which precision is greater than 0.01; 2) the coverage area for prediction is below 1.5\( km^2 \); 3) random one point crossover for each chromosome pair with probability \( P_c = 40\% \); 4) random mutation of genes in the population with probability \( P_m = 0.01 \);

The number of individuals in each generation is decided by the number of the pixels after the appointed coverage area has been discretized, and the iteration is stopped to output the solution when the algorithm continues with the same best chromosome for 50 iterations. The survivors are selected for mating during selection and generate offspring in crossover. The last operation is mutation for introducing the traits not in the population. The iteration stops to output the solution if the algorithm continues without improvement.

C. Cell Coverage Reconstruction

After obtained the distribution of the propagation loss factors within the area by the simple genetic algorithm, the local mean of received power in any position within this area can be predicted:

\[
\hat{P}_i = \hat{P}_i^{(A)} - \sum_{j=1}^{N} D_{ij}\alpha_j \tag{6}
\]

where \( i \in [1, N], j \in [1, N] \), \( \hat{P}_i \) is the predicted local mean of the received power in the j-th pixel, \( D_{ij} \) is the length of the line segment, where the i-th virtual propagation path intersects the boundary of the j-th pixel, and it represents the weight
of the j-th pixel to the total propagation loss, if there is no intersection between the i-th virtual propagation path and the j-th pixel, $D_{ij}$ takes zero value; $P_i^{(4)}$ is the real measured data in the nearest intersection of the i-th virtual propagation path and the boundary of the area from this BS.

III. THE FLOWCHART OF COVERAGE PREDICTION

The flowchart of the cell coverage prediction is shown in Fig. 1 and contains five major modules, such as Data Preprocess Module, Integral Equation Construction Module, GA Solution Module, Cell Reconstruction Module and Prediction Evaluation Module. The main functions of those modules are as follow:

1. Data Preprocess Module: it contains a filtering preprocessor to ultimately remove fast fading and derive the average value of the received power. This module also emendates GPS errors and wipes off invalid records in the measured data. The checking samples can not be participated in the coverage prediction and just be used to evaluated the quality of the model.

2. Integral Equation Construction Module: it is responsible for construction of the inversion problem for the propagation loss factor distribution, and discretization of integral equation (Eq. (3)).

3. GA Solution Module: it is used to solve Eq. (5) by the GA method and get the propagation loss factor distribution.

4. Cell Reconstruction Module: the prediction result of cell coverage is reconstruction by Eq. (6) based on the the propagation loss factor distribution solved.

5. Prediction Evaluation Module: The predicted error of the proposed model is defined by $\varepsilon_i = P_{Mi} - P_{Pi}$, $i \in [1,2,...,q]$, in which $\varepsilon_i$ is the predicted error for the i-th checking sample, $P_{Mi}$ is the measured value for the i-th checking sample after removing its small-scale fading, $P_{Pi}$ is the i-th predicted value at the same locations, $q$ is the number of the checking samples. The average deviation $\mu$ (dB) and standard deviation $\sigma$ (dB) are selected to evaluate the prediction quality.

The remaining modules in Fig. 1 are mainly used to analysis the reason and correct the prediction results by some prior knowledge and empirical formulas when the results are not ideal. For the limitation of paper length and they are not the focus of this paper, the detailed process of those models are not described particularly in this paper.

To reconstruct the distribution of the received power within a region, the size of the pixel should be chosen in the first instance, and the their minimum size is dependent on the window length of the spatial filtering, for example, it is about 12m in 900MHz. It was validated that the prediction errors for all cells had vibrated slightly when the pixel’s size increases from $10 \times 10$ to $40 \times 40m^2$ under the same condition, but the computational time obviously shortened. Generally, the computational time would be within 1 minute for a region with the area of one square kilometer under the pixel size of $20 \times 20m^2$. In the following calculations, the pixel size is taken as $20 \times 20m^2$.

IV. EXAMPLES OF CELL COVERAGE PREDICTION

A. The Measurement Set-up

Measurements were carried out at 900MHz in GuangDong, China. The received signals came from the base stations of an operating GSM network. During measurements, the base stations all remained in the fixed position with directional transmitting antennas, which type and transmitting power are slant \(\pm 45\degree\) dual polarization and +43dBm, respectively. The heights of the cells’ antenna are around 30m, which are located higher than that of the almost all surrounding buildings within the predicted area. The appointed cell can be identified uniquely through BCCH (Broadcast Control Channel) and BSIC (Base Station Identity Code).

A dual-band scanning receiver, with the maximum sampling rate of 300 samples/s for scanning a single frequency, was used for getting instantaneous values of the received power, and a GPS receiver was used to locate the coordinates of the moving scanning receiver. The receiving antennas were placed on the top of the test car with a height of 2.5 m above the ground. The speed of the car in the course of measurements was kept at about 30km/h, and the sampling rate would be at least 40 samples per second with simultaneous scanning three different frequencies, which completely meet the requirement of Lee’s criterion for estimating the means[6].

B. Predicted Results and Evaluation of Region I

Fig. 2 illustrates the experimental scenario in an urban environment in the later spring of 2005 in order to compare with the predicted results in [4], which is called region I. In Fig. 2, the solid bold lines denote the boundary of the predicted area, while the broken lines represent the measured routes along the periphery of the area, whose data are used to predict the distributions of signal powers within the region, and those dashed lines within the area indicated by “+” marker stand for the checking routes, whose data will enable the quality of the proposed model to be evaluated. The letters Cell A, B, and C...
are codes of the appointed base stations which locations are denoted by the triangle symbols.

Experiments were carried out for regions I as the example applying the proposed model to the coverage prediction by GA method and comparison with CT method in [4]. For region I, there are totally 1468 pixels for the predicted area, and then there are 258, 282 and 287 valid rays for cell A, cell B and cell C respectively. There are two different checking routes, the R1 and R2, within region I and the total checking sample number is 195 for each of three cells. The checking samples were divided into two groups according to the orientation of checking routes. One of them was numbered from 1 to 125 relating to the checking route R1 and another from 126 to 195 relating to the checking route R2 (see Fig. 2).

In order to verify the stability of the coverage prediction for the given cells by the proposed model, the measurements along the periphery of the region were repeated for four times in the same manner as mentioned above, which are measured in 16:00 on 17/4/2005 (noted in the letter “I” in Table I), 16:30 on 17/4/2005 (“II”), 10:00 on 19/4/2005 (“III”) and 10:30 on 19/4/2005 (“IV”) respectively, while the checking samples remained the same as the first one.

Table I lists \( \mu \) and \( \delta \) of the predicted errors of the checking samples for cells A, B and C in Fig. 2, which are predicted by GA method and CT method respectively. It can see that \( \delta \) are below 5 dB and \( \mu \) are less than 2 dB for all three cells and all four measurements by the GA method, which results are better than those by the CT method. Furthermore from results listed in Table I, it can be seen that the variation extension of the average deviations and standard deviations for the repeated experiments are quite small, implying the stability of coverage distributions predicted by applying the proposed model. However, they are not representative of the variation caused by the change of the urban propagation environment in a long time scale because the time interval of repeat experiments made in this study is only a few days.

Fig. 3 (a), (b) and (c)) illustrate the comparison of the average values of measured powers for checking samples and predicted powers at the same location which were plotted versus sequence number between the GA method and CT method. The prediction powers shown in Fig. 3 were obtained with the reconstruction using the data measured at 15:00 on 15 April, 2005 along the periphery of this area.

For three cells, a good agreement is seen between the predictions by the GA method and measurements as shown in Fig. 3 (a), (c) and (e), for both R1 and R2 (see Fig. 2). The absolute errors exhibit a step-down trend, and the absolute error of 90% checking samples is below about 8 dB (see Fig. 3 (b), (d) and (f)), which is better than those by the CT method.

C. Predicted Results and Evaluation of Region II

The region II is another example measured in the 15:20 on 18/5/2006, for which Cell F is located inside of the predicted area. Measurements were carried out for region II as the example applying the proposed model to the coverage prediction by GA method and comparison with CT method in [4]. For region II, there are totally 283 pixels for the predicted area, and then there are 87, 72 and 70 valid rays for cell A, cell B and cell C respectively. There are two different checking routes, the R1 and R2, within region II and the total checking sample number is 195 for each of three cells. The checking samples were divided into two groups according to the orientation of checking routes. One of them was numbered from 1 to 125 relating to the checking route R1 and another from 126 to 195 relating to the checking route R2 (see Fig. 2).

In order to verify the stability of the coverage prediction for the given cells by the proposed model, the measurements along the periphery of the region were repeated for four times in the same manner as mentioned above, which are measured in 16:00 on 17/4/2005 (noted in the letter “I” in Table I), 16:30 on 17/4/2005 (“II”), 10:00 on 19/4/2005 (“III”) and 10:30 on 19/4/2005 (“IV”) respectively, while the checking samples remained the same as the first one.

Table II lists \( \mu \) and \( \delta \) of the predicted errors of the checking samples for cells A, B and C in Fig. 2, which are predicted by GA method and CT method respectively. It can see that \( \delta \) are below 5 dB and \( \mu \) are less than 2 dB for all three cells and all four measurements by the GA method, which results are better than those by the CT method. Furthermore from results listed in Table II, it can be seen that the variation extension of the average deviations and standard deviations for the repeated experiments are quite small, implying the stability of coverage distributions predicted by applying the proposed model. However, they are not representative of the variation caused by the change of the urban propagation environment in a long time scale because the time interval of repeat experiments made in this study is only a few days.

Fig. 3 (a), (b) and (c) illustrate the comparison of the average values of measured powers for checking samples and predicted powers at the same location which were plotted versus sequence number between the GA method and CT method. The prediction powers shown in Fig. 3 were obtained with the reconstruction using the data measured at 15:00 on 15 April, 2005 along the periphery of this area.
The average received power from Cell F in the predicted area. (see Fig. 5 (b)). Fig. 6 describes the prediction distribution of the Cell F, and the absolute error of 90% samples is below 8dB predictions and measurements is met for all checking routes of manner as Fig. 3. It can be noticed that the agreement between errors for the Cell F. Fig. 5 (a) was plotted using the same occurrence and cumulative percentage of absolute prediction powers at the same location and the statistical percentage of measured powers for checking samples and that of predicted respectively, which only spends a few minutes for prediction.

The total numbers of the checking samples for Cell F is 321. The $\mu$ and $\sigma$ of the predicted error is 0.48 dB and 4.81 dB respectively, which only spends a few minutes for prediction.

Fig. 5 illustrates the comparison between the average values of measured powers for checking samples and that of predicted powers at the same location and the statistical percentage occurrence and cumulative percentage of absolute prediction errors for the Cell F. Fig. 5 (a) was plotted using the same manner as Fig. 3. It can be noticed that the agreement between predictions and measurements is met for all checking routes of the Cell F, and the absolute error of 90% samples is below 8dB (see Fig. 5 (b)). Fig. 6 describes the prediction distribution of the average received power from Cell F in the predicted area.

Fig. 4. Schematic diagrams of the experimental scenario for Region II.

Fig. 5. Comparisons of the average values of measured powers of checking samples and that of predicted powers at the same location, and the statistical percentage occurrences of absolute prediction errors and their cumulative percentages for Cell F by GA method.

Furthermore, to evaluate the applicability of the proposed model in different areas, adding experiments were carried out in different radio environments (such as the inshore area and suburban, etc) of GuangDong, China. The average deviations for predicted averages are in the range of 2dB and the standard deviations are 4-6dB almost. The details of results have not been given because of restriction in the length of the paper.

V. CONCLUSION

In this paper, a novel method of coverage prediction based on measurement is proposed as an inverse problem. So we have simplified a complicated propagation prediction problem to a system of large scale ill-condition equations, which can be solved by genetic algorithm appropriately. Examples of coverage prediction show that, with very low computational cost and without the help of a digital map, $\mu$ and $\delta$ of the predicted averages obtained by the proposed method are in the range of 2dB and 4-6dB, respectively.

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