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Field Strength Data Processing for Wireless Mobile Communication Based on Genetic Algorithm Applied to Least Square Polynomial Fitting

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Abstract. In wireless communication system, the signal strength is one of the basic parameter to assess the coverage by the base station antenna. Diverse methods can be used to collect or estimate this information for the design and optimization of mobile communication system**.** This paper focuses on the field strength data processing where an appropriate model which is the polynomial fitting that is a best fit (in a least-squares sense) for field strength data, then the study is reformulated as a problem of optimization where genetic algorithm (GA) is further used to adjust the model coefficients that the aim is to more minimize the error between the estimated field strength and measured field strength data and match them as close as possible. The field strength data which will be processed is estimated by ray tracing technique based on three-dimensional geometric theory, geometrical optics theory and the uniform theory of diffraction (UTD). The polynomial fitting and genetic algorithms are coded in MATLAB software and the display of results is accomplished using MapInfo interface .The result of simulation is compared with measured data that obtained using devices.

Keywords: Mobile Communication, Ray Tracing, Grid Partitioning, Field Strength Processing, Least Square Polynomial Fitting, Genetic Algorithm.

1. Introduction

In the network planning and optimization of mobile communication, cellular signal strength estimate results not only determine the rationality of the planning results, but also affect the quality of the network optimization, so designing accurate signal strength estimation methods is the key problem of mobile communication network research.

In this paper, we describe a realization of the cell field strength estimation system software[1] designed using Visual Studio as a debugging environment, C++ as the development language, MapInfo as secondary development tools on MFC interface (Microsoft Foundation Classes), and SQL server to access the database[1]. This system software is based on ray tracing which is suitable for outdoor scenes, and it is based on a method that divides the space into grids, records the grid number each ray passes, finds the intersection with buildings, and determines all the routes of ray tracing combined with iterative process, then the field strength of each grid will be calculated, the ray tracing method is based on three-dimensional geometric theory, geometrical optics theory and the uniform theory of diffraction (UTD) [2].Then the paper is concerned on the processing of signal strength estimated by ray tracing technique using genetic algorithm (GA) applied to least squares polynomial fitting. The aim is to minimize the error between the estimated

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field strength and the measured in the same environment and match them as close as possible, and simulation results are compared with real measurements achieving good results with very low levels of difference errors.

Polynomial fitting plays an important role in the analysis, interpretation, and correlation of experimental data. Although there are many approaches to polynomial fitting, the method of least squares can be applied directly to problems involving linear forms with undetermined constants. However, the conventional least squares method of curve fitting does have limitations; nonlinear forms and forms for which no derivative information exists present problems. These limitations may be overcome by incorporating a GA. GA's are search algorithms based on the mechanics of natural genetics[3]. They efficiently exploit old knowledge contained in a population of solutions to generate new and improved solutions. GA's have been used in a variety of problems [4], [5] where they have been shown to converge rapidly to near-optimal solutions after having sampled but a small fraction of the search space. In this paper, a simple GA is applied to first degree least squares polynomial-fitting.

2. Formulation of the Problem

2.1. Data description

The first task of this paper is the implementation of cellular signal strength estimation system interface [1] in English version figure1. The system consists of three parts: data storage and the processing subsystem, the signal strength estimation subsystem and the display subsystem. The data storage and processing subsystem parses imported files of maps and base stations which are stored in the database and deals with them according to the need of the ray tracing algorithm. The signal strength estimation subsystem uses an estimation method based on forward tracing to calculate the signal strength distribution of the base station. The display subsystem shows imported data, processed data and estimation results by calling the MapInfo interface. The main interface of this system is shown in Fig.1

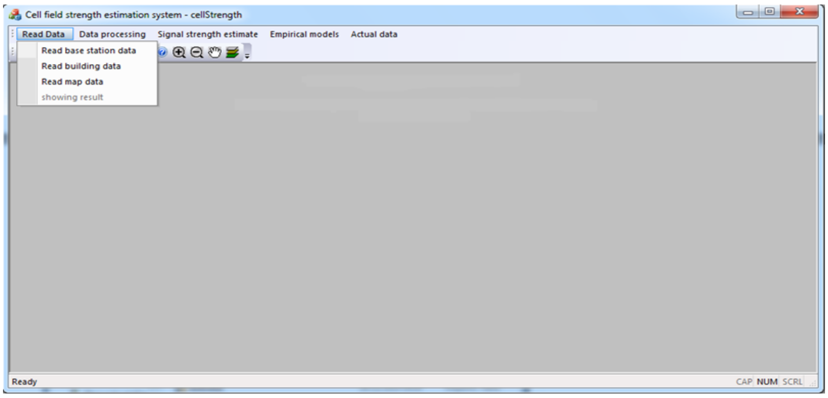


Fig.1: Main interface of the system

2.2. The geographical environment modeling

The campus of Beijing University of Aeronautics and Astronautics is chosen as the study area, the range is 1305m*1375m using the mesh method, and the cell is divided into a 5m * 5m grids. This makes a total of 261*275=71775grids.

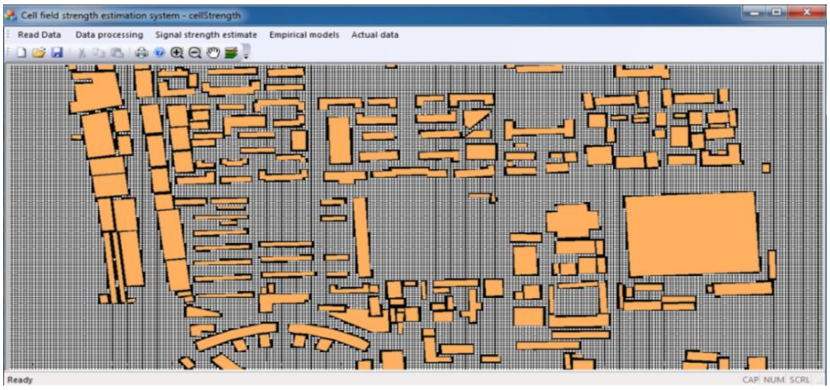


Fig.2: The study area is divided into a grid after a two-dimensional map

2.3. System operating results

The system operating results are ray tracing results which are the field strength values within the grid. The field is divided into several small power ranges represented by a different color. The base station is located in building N°3 (blue dots) as shown in figure 3,it is an antenna with azimuth angle of 260 degrees, a decline angle of 10 degrees and the radiation frequency is 900MHz.

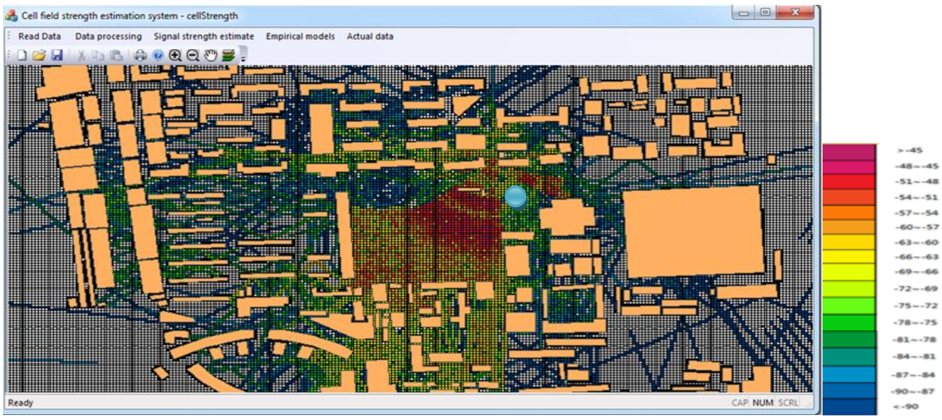


Fig.3 : Cell field strength estimate inside the campus based on ray tracing

Dealing with the results we find that they are not so close to real data, so that is what led us to design a methods to match them where the aim is to minimize the error between the estimated field strength and the measured data in the same environment and match them as close as , this task is presented in the next section

2.4. Field strength data processing based on genetic algorithm applied to least square polynomial fitting.

2.4.1 Least square polynomial fitting

In this section we select an appropriate model which is the polynomial fitting that is a best fit (in a least-squares sense) for field strength data, then genetic algorithm is incorporated to adjust the model coefficients that the aim is to more minimize the error between the ray tracing field strength and measured field strength data and close them as close as possible.

In our case we choose linear least squares method to fit a linear model to data. A linear model is defined as a first degree polynomial. For the illustration of the linear least-squares fitting process [6],[7],[8], we suppose that we have *n* datasets (in our case n field strength data) that can be modeled by a first-degree polynomial:

$$y = P_1 x + P_2 \qquad (1)$$

y : measured data

x : ray tracing field strength data

p1, p2: coefficients to be found by least square method

After finding the model coefficients, where this task is accomplished using the Matlab polyfit function, we apply genetic algorithm to further get best fit to the measured data.

2.4.2 Genetic algorithm

Genetic algorithm is a powerful search algorithm that performs an exploration of the search space that evolves in analogy to the evolution in nature. They use probabilistic transition rules instead of deterministic rules, and handle a population of potential solutions known as individuals or chromosomes that evolves iteratively [9]. Iteration of the algorithm is termed as generation. The evolution of solutions is simulated through a fitness function and genetic operators [9]. The fitness function plays a very important role in guiding GA to obtain the best solutions within a large search space. Good fitness functions will help GA to explore the search space more effectively and efficiently. Bad fitness functions, on the other hand, can easily make GA get trapped in a local optimum solution and lose the discovery power.

The procedure of genetic algorithm begins by creating an initial random population of *M* individuals or chromosomes. Each chromosome represents the coding of a data set *P*, where:

$$P = (p1, p2, \dots \dots \dots \dots, pL \quad (2)$$

This data set corresponds to a potential solution to the problem to be solved. The generation of a new population from the preceding one is carried out in three stages.

a) Evaluation: the fitness function is estimated for all the chromosomes in the current population, based on certain characteristics that are desired in the solution. In our problem the fitness used is chosen as the mean square error described in the equation (2):

$$F(p_1, p_2) = \frac{1}{N}\sum_{n=1}^{N}\left(y_n - (p_1 x_n + p_2)\right)^2 \quad (3)$$

y : measured data

x : ray tracing field strength data

p1, p2: coefficients to be adjusted by genetic algorithm

The best data set, corresponding to the best chromosome in the population of the *g*th generation, belongs to the smallest *F*. The fitness function represents the only link between the physical problem and the GA.

b) Selection: after the evaluation of every chromosome in the population, the selection is applied. Two parents are generated by one of the selection methods. In our case, the determinist selection is adopted. The GA selects the individuals that optimize best the fitness function.

c) The reproduction by crossover (Fig. 4) and mutation (Fig. 5) is then performed on the selected parents to generate two children that replace their parents in the new population. Mutation is carried out by randomly changing one or more genes (variables) of the created offspring. It is used for maintaining certain diversity in the population. The proposed algorithm applied the one-point crossover method

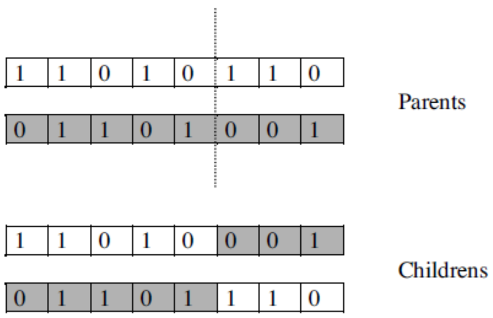


Fig. 4: Schematic representation of the one-point crossover

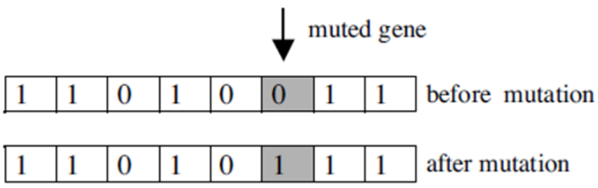


Fig. 5: Schematic representation of a mutation in a chromosome.

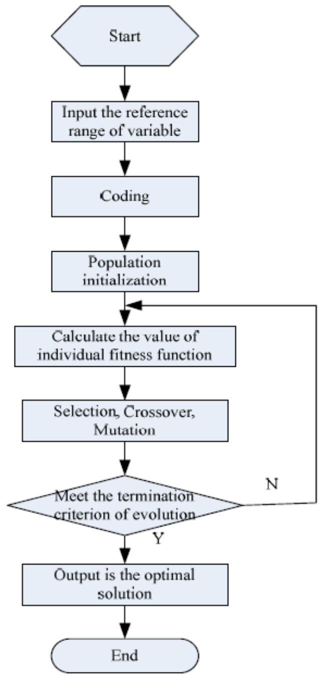


Fig. 6: Flowchart for the GA.

According to the evolutionary theory, this new generation will be more adapted to the problem than the preceding one. The evolution process is reiterated until satisfaction of a certain halting criterion or if a total number of generations is reached. A flowchart of the basic GA is shown in Fig.6

The essential characteristic of genetic algorithms is the coding of the variables that describe the problem. From a computational point of view, we use in our algorithm a binary coding. Note that we could also use other forms of coding (real, Gray coding ...) [10]. Each chromosome contains a number of genes, corresponding to a number of unknown variables. Recall that in our study the n variables are assumed to be real. We consider a finite search space: In order to encode our real variables in binary, we discretize the search space. Thus k-bit encoding involves a discretization of the search interval in gmax = 2^k-1 discrete values, k is the length of the gene i.

To each real variable pi we thus associate a long integer g_i:

$$0 \leq g_i \leq g_{max} \qquad \forall i \in [1 \quad n]$$

The coding formulas are then as follows [11]:

$$g_i = \frac{p_i - p_{imin}}{p_{i\,max} - p_{i\,min}} g_{max} \tag{4}$$

Where $p_{i\,min}$ and $p_{i\,max}$ are the limits of the research interval, and they are determined by prior knowledge of the model. These limits are obligatory to fix in order to avoid unreasonable parameters [12].

3. Numerical Results and Discussion

To start up with GA, certain parameters must to be defined. It contains the bit length, population size of chromosome, quantity of iterations, selection, crossover and mutation types etc. Initializing the values of the parameters for work is as follows:

- Population size : 100
- Bit length of the considered chromosome:6
- Number of Generations: 20
- Selection method: “determinist selection”
- Crossover type: “Single point crossover”
- Crossover probability: 0.7
- Mutation type: “Uniform mutation”
- Mutation probability: 0.01

We are applying polynomial fitting using one degree linear polynomial. The polynomial coefficients are calculated based on the Matlab Polyfit function, and then they are adjusted by the use of genetic algorithm:

Table 1, summarize the polynomial fitting results before and after using the genetic algorithm , Figure 7 shows the best -of-generation error (variation of the fitness function) and Figures 8 shows the comparison between the field strength data processed and the measured data .

Table 1: The polynomial fitting coefficients before and after using the genetic algorithm

Polynomial Coefficients	Before Optimization through GA Algorithm	After Optimization through GA Algorithm
$\mathbf{P_1}$	0.0354	0.0426
$\boldsymbol{P_2}$	-54.255	-61.825

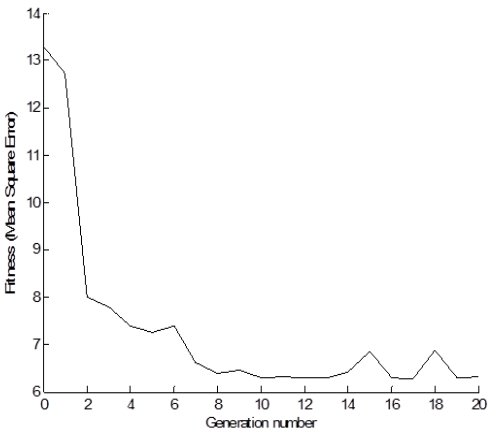
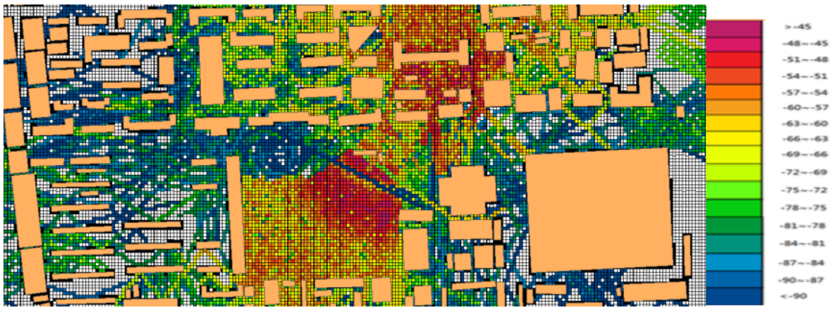
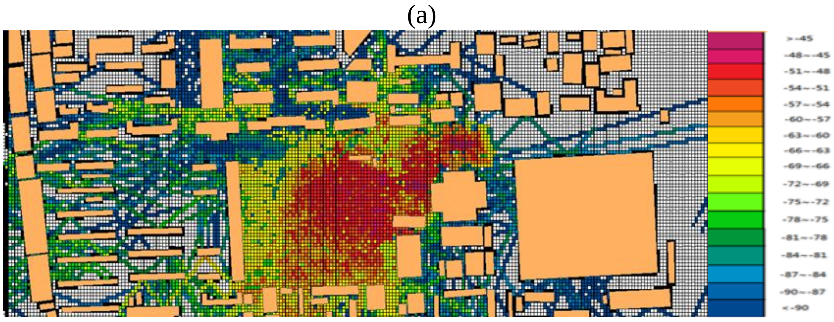


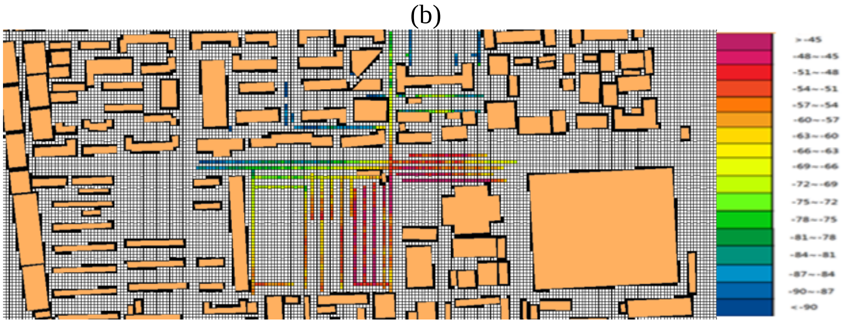
Fig. 7: The best –of-generation error



(a)



(b)



(c)

Fig. 8: comparison between: (a) field strength estimated by ray tracing, (b) Processed field strength data using GA applied to least square and (c) Measured field strength data

Comparing the processed field strength distribution with the measured data, we find that in both dense areas and open areas away from the buildings, there is good agreement.

4. Conclusion

This paper presents an approach for processing of the field strength data using genetic algorithm (GA) applied to least squares polynomial fitting .The estimation of field strength data was estimated by the ray tracing method. The GA is employed to adjust the choice of the polynomial fitting coefficients by minimizing a mean square error function. Results show that the implementation is proved to be accurate by comparing the simulation results with measured data, and they serve as a demonstration of the GA. versatility and power in the area of least square polynomial fitting.

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