Research on the Construction of Radio Environment Map (REM) Based on Spatial Interpolation

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Abstract. For the further performance improvement of Cognitive Radio systems, providing accurate or comprehensive information support to Cognitive Radio devices or networks, there is a use of "Radio Environment Map (REM)", which presents multi-dimensional information of radio environments and scenarios. With the study of Spatial Interpolation, a method of constructing REM is proposed, and the performance of each algorithm is compared. Experiments show that the RMSM algorithm has advantages like high efficiency and low error, which can be used for the construction of REM.

Keywords: Radio Environment Map · Cognitive Radio · Spatial Interpolation

1 Introduction

Currently, promoting dynamic spectrum management (DSM) has become an international trend. Cognitive Radio (CR), breaking the traditional frequency distribution mechanism which was closed or protected, which enabling the dynamic sensing of spectrum environment by wireless devices or systems, making the spectrum access more efficient and flexible [1]. For the further performance improvement of Cognitive Radio systems, the technique "Radio Environment Map (REM)" appears.

Radio Environment Map (REM), proposed by Y.P. Zhao in 2005, is a comprehensive spatiotemporal database and an abstraction of real-world radio scenarios [2], which presents multi-dimensional information of radio environments. Now the concept of REM has been acknowledged by the international group "Wireless Innovation Forum" and referenced by several standard documents such as IEEE, ITU-R, ETSI [3]. The objective of the project FARAMIR (Flexible and Spectrum-Aware Radio Access through Measurements and Modelling in Cognitive Radio Systems), conducted by Framework Program 7 (FP7) in 2010, is to research and develop a complete REM prototype system for increasing the radio environmental and spectral awareness of future wireless systems, improving the capacity or innovation of radio resource optimization and radio management in European industry [4–7]. In recent years, many colleges or institutions have conducted the research on the techniques of spectrum management based on REM [8–12].

Spatial Interpolation is a method to evaluate the unknown point and fill the blank space by using the sample point [13], which is widely applied to Geographic

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Information System (GIS), image processing, indoor positioning and so on. The techniques of Spatial Interpolation, which are commonly used, include Inverse Distance Weighting (IDW) [14, 15], Natural Neighbor [13], Spline Interpolation [16], and Kriging Interpolation [17]. In this paper, Spatial Interpolation algorithm are compared and used for analyzing the radio environment, and a method of constructing the REM based on Spatial Interpolation and Received Signal Strength (RSS) is proposed.

The rest of this paper is structured as follows. Section 2 explains the general model and classic method of Spatial Interpolation and the modified algorithm called RMSM. Section 3 provides the algorithm procedure and complexity analysis of RMSM, while Sect. 4 presents the experiment and comparison. Finally, Sect. 5 concludes the paper.

2 Spatial Interpolation

2.1 General Model and Classic Method

Spatial Similarity is the basic ideal of Spatial Interpolation, that is to say, in terms of an unknown point, the closer to the sample data point, the more similar to the sample point. As it is shown in Fig. 1, the general model of Spatial Interpolation can be depicted with the subsequent formula:

$$P(x_0, y_0) = \sum_{i=0}^{N} \omega_i(x_0, y_0) \cdot P(x_i, y_i) \tag{1}$$

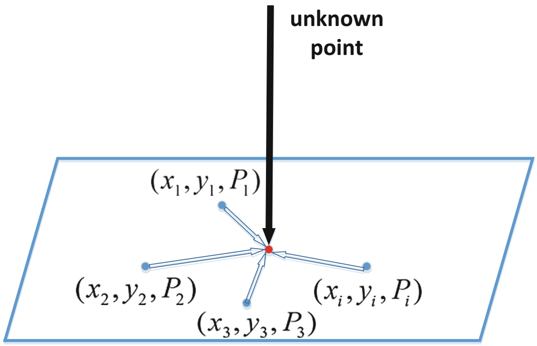

Fig. 1. Schematic diagram of Spatial Interpolation

Here, $P(x_0, y_0)$ is a certain estimated value of the location (x_0, y_0), $P(x_i, y_i)$ is known value at the point (x_i, y_i), and $\omega_i(x_0, y_0)$ is the weight assigned to the interpolation point (x_0, y_0) by the sample data point (x_i, y_i).

IDW classic method, introduced by Shepard in 1968 [14], is a local method, in which interpolation value is influenced by all of the data. That is, the method regards the weights as the negative exponent of distances and uses all the available sample data (N) to perform the interpolation:

$$\begin{cases} \omega_i(x_0, y_0) = \frac{1}{d_i^{dexp}} \\ d_i = \sqrt{(x_i - x_0)^2 - (y_i - y_0)^2} \\ (i = 1, 2, \ldots, N) \end{cases} \tag{2}$$

Here, d_i is the Euclidean distance between each sample data point and the interpolated point (x_0, y_0) and d_{exp} is the distance exponent. Simple and widely used as the method is, but the drawbacks like large amount of computation are obvious. The local method of Modified Shepard's Method (MSM), proposed by Renka [15], is the main enhancement compared to the IDW classic method. By defining the influence radius R, only the sample data points in a circle of it around the interpolation point are taken into consideration. Then the weights are modified by:

$$\omega_i(x_0, y_0) = \begin{cases} \left[\frac{(R - d_i)}{R \cdot d_i}\right]^{d_{exp}}, & d_i \leq R \\ 0, & d_i > R \end{cases} \tag{3}$$

The optimal condition of this method is all the sample data point are distributed into square grid.

2.2 Revised Modified Shepard Method (RMSM)

Through the research on MSM, this paper presents a Revised Modified Shepard Method (RMSM) algorithm, which is improved as follows:

1. Optimizing the weights. The sample data points (x_i, y_i) are not always well-distributed in REM scenarios. For example, when sample data points are few or not uniformly distributed, the weights assigned to interpolation point fail to be reasonable. Hence, relative weights ω_i' are defined by:

$$\begin{cases} \omega_i' = \frac{\omega_i}{\omega_0} \\ \omega_0 = \left[\frac{R - \min(d_i)}{R \times \min(d_i)}\right]^{d_{exp}} \\ (i = 1, 2, \ldots, N) \end{cases} \tag{4}$$

where ω_i is still calculated by (3) and ω_0 is the weight assigned by the shortest point.

2. Flexibly using the local features. The aim of nodal function $Q(x, y)$ fitting by local data points, introduced in MSM method, was to optimize the weight of a certain point (x_i, y_i) using other neighbor point within the influence radius R. However, there are several limitations of MSM method to choose R in actual REM scenarios when sample data points are undesirably distributed (e.g. centralized on one point) such as few or no data points within the R. RMSM method solves this problem by selecting a certain number of neighbor points—N_q for nodal function fitting, while N_W for weights calculating to interpolate.

The nodal function $Q_k(x, y)$ of a sample point (x_k, y_k) in a two-dimensional surface could be could be various form (linear, quadratic etc.). Here, to fit the radio propagation, RMSM method chooses the quadratic form to $Q_k(x, y)$ fitting:

$$Q_k(x,y) = c_{k1}(x - x_k)^2 + c_{k2}(x - x_k)(y - y_k) + c_{k3}(y - y_k)^2 \\ + c_{k4}(x - x_k) + c_{k5}(y - y_k) + P_k \tag{5}$$

coefficients $c_{k1}, c_{k2}, \ldots, c_{k5}$ are performed by the principle of LMS (Least Mean Square) as:

$$\underset{Q_k(x,y)}{\arg} \min\left\{\sum_{i=1}^{N_q} \omega_j'(x_k, y_k)\left[Q_k\left(x_j, y_j\right) - P\left(x_j, y_j\right)\right]^2\right\} \\ (j = 1, 2, \ldots, N_q \\ k = 1, 2, \ldots, N_w) \tag{6}$$

where $Q_k\left(x_j, y_j\right)$ denotes the output of the point (x_k, y_k) at one of its neighboring point $\left(x_j, y_j\right)$, while $\omega_j'(x_k, y_k)$ is the relative weight of (x_k, y_k) assigned by the point $\left(x_j, y_j\right)$, which is also calculated by (3) and (4), replacing the R/d_i with R_q/d_j or R_W/d_k in (7):

$$\begin{cases} R_q = \max(d_j), & j = 1, 2, \ldots, N_q \\ R_W = \max(d_k), & k = 1, 2, \ldots, N_w \end{cases} \\ 1 < N_q, N_w \le N \tag{7}$$

Here, as it is vividly depicted in Fig. 2, d_j refers to the Euclidean Distance between a sample point (x_i, y_i) and one of its N_q neighboring point $\left(x_j, y_j\right)$, while d_k is the distance between the interpolation point (x_0, y_0) and one of its N_w neighboring point (x_k, y_k). N_q and N_w could be equal or not because there is no relationship between them.

3. Efficiently neighbor searching. To find N_w neighboring points of interpolation point (x_0, y_0) and its N_q neighboring points for nodal function fitting, RMSM method makes the Near Neighbor (NN) searching twice by constructing the KD-Tree data structure. KD-Tree (k-Dimensional Tree) is a special binary tree, which is widely used for range searing [18]. Through the spatial division by hyperplanes, instead of time-consuming method that traverses all data point, KD-Tree conducts the NN searching only by backtracking of its sub-tree. After the searching, the RSS of N_w data points are optimized as

$$f_k = \frac{1}{N_q} \sum_{j=1}^{N_q} Q_k\left(x_j, y_j\right) \tag{8}$$

Finally, the interpolation value of the point (x_0, y_0) is calculated using

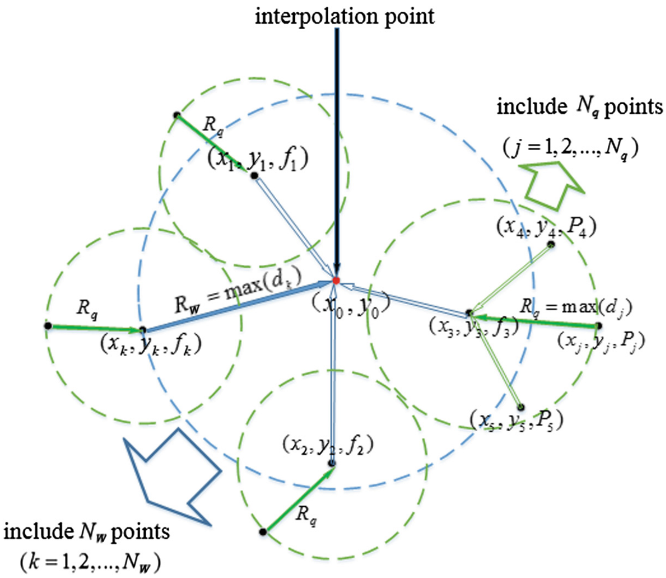

Fig. 2. Schematic diagram of RMSM algorithm

$$P(x_0, y_0) = \sum_{k=0}^{N_w} \omega_i'(x_0, y_0) \cdot f_k \quad (k = 1, 2, \ldots, N_w) \tag{9}$$

In practice, it is difficult to get the best result of Spatial Interpolation—expanding the discrete data into surface data, but the substitutional way of interpolation gridding is always used. That is, defining the space as a grid are at a certain resolution (size of the grid), and interpolating for each grid point. The construction of Radio Environment Map (REM) is right a case of expanding the measurement data points into a RSS surface.

3 Algorithm Process and Complexity

3.1 Algorithm Process

1. Input

① RMSM algorithm related parameters:

$$N, d_{exp}, N_q, N_w$$

② Grid area related parameters:

$$X_{min}, X_{max}, Y_{min}, Y_{max}$$
$$\text{Number of grid points: } M = X_{points} \times Y_{points}$$

(X_{points}, Y_{points} denotes the number of grid point on X and Y coordinates axes)

2. Initialization

① Data points matrix ***points***:

$$\text{double[,]points} = \text{new double[N,3]}$$

filled by the values as follows:

$$\boldsymbol{points} = \begin{bmatrix} x_1 & y_1 & P_1 \\ & \vdots & \\ x_N & y_N & P_N \end{bmatrix}_{N \times 3}$$

② Weights matrix $\boldsymbol{\omega}'$ and outputs matrix of nodal function $\boldsymbol{q}$:

$$\begin{aligned} &\text{double[]w1} = \text{new double[Nq]} \\ &\text{double[]w2} = \text{new double[Nw]} \\ &\text{double[]q} = \text{new double[Nw]} \end{aligned}$$

③ Grid points (all of the interpolations for the construction of REM) matrix ***XY***:

$$\text{Double[,]XY = new Double[xPoints, yPoints]}$$

3. Constructing the two-dimensional KD-Tree in ***points***
4. Starting with the first grid point ($m = 1$) and repeating the steps of ①–③ as follows:

① NN searching for N_w neighboring points and weights calculating by (4), hence

$$\boldsymbol{\omega}' = \begin{bmatrix} \omega_1' & \ldots & \omega_{N_w}' \end{bmatrix}$$

② NN searching again for N_q neighboring points and nodal function fitting by (6), filling the matrix $\boldsymbol{q}$:

$$\boldsymbol{q} = [f_1 \quad \cdots \quad f_k \quad \cdots \quad f_{N_w}]^{\boldsymbol{T}}$$

③ Calculating the interpolation value of present grid point by

$$result = \boldsymbol{\omega}' \cdot \boldsymbol{q}$$

5. Until the last grid point ($m = M$) is calculated, the RMSM algorithm is ended up with M outputs for the REM construction.

3.2 Complexity Analysis

IDW Classic is a global method that uses all known points to interpolate, it requires $O(N)$ when N points are measured, and the complexity will reach $O(MN)$ for REM construction. While MSM and RMSM are local method (the number of local points $N' < N$ in most general case, which is depended on R and N_q/N_W choosing), use the NN searching, required $O(logN)$, for local points. Both of them need $O(MlogN)$ complexity.

Undoubtedly, it is obviously improved of MSM and RMSM method, compared to IDW Classic, on computational efficiency and, the denser of the grid, the closer to continuous data surface the REM is, but the greater processing requirements needed.

4 Experiments and Analysis

4.1 Experimental Scenario

There are six routers placed in an 15m × 20m indoor area (AP1–AP6 in Fig. 3), where some Non-Line-of-Sight propagation condition like walls or obstacles existed. Each router could transmit 2.4 GHz WIFI signal, and the RSS values are measured by cellphone.

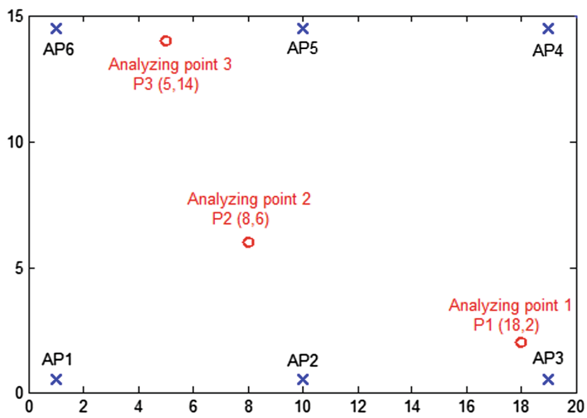

Fig. 3. Schematic diagram of experimental scenario

All the algorithms this paper mentioned are implemented by C# in Visual Studio 2010, and the related data are stored in SQL Server 2008. A total of six kind of scenarios (combinations of 6 routers) are tested, RSS (dBm) from 50 different positions are measured in each scenario. After that, choosing three points (analyzing point P1–P3 in Fig. 3) to calculate the interpolation value (performing calculation $3 \times 6 = 18$ times each analyzing point) using the algorithms above. Parameters setting as Table 1.

Table 1. Experimental parameters settings

Parameters	Values
Distance exponent d_{exp}	1
Number of sample points N	Exp.1: 30 Exp.2: 50
R (for MSM method)	6(m)
$Q(x, y)$	Quadratic
N_q	Exp.1: 18 Exp.2: 30
N_w	Exp.1: 24 Exp.2: 40

4.2 Performance Evaluation

Figure 4 presents the error bars of three methods mentioned above (IDW Classic, MSM, RMSM) in different sample points N. Specifically, the histograms denote the MAE (Mean Absolute Error) of each methods:

$$MAE = \frac{\sum_{i=1}^{N} |P_m - P_c|}{S} \tag{10}$$

where P_m, P_c refers respectively to RSS value of measurement and estimation, and S is experimental times ($S = 18$ in this section). The line-segments represent the standard deviation, which indicate the robustness of each methods by the length.

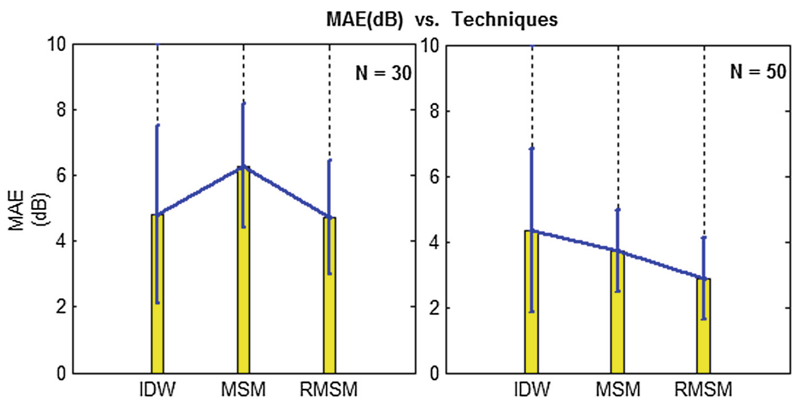

Fig. 4. Comparison of algorithms

Obviously, IDW Classic method refers the relatively high MAE and poor robustness due to the use of all sample points and its low computational efficiency, and the existence of certain measurement error is also a factor inevitably; MSM method shows the poorest MAE performance when sample data points are less (left sub-diagram in Fig. 4), though it gets the better robustness than IDW Classic method; By optimizing the weights and flexibly using the local feature, depicted in Fig. 4, RMSM method improves approximately half of the robustness (50.4%, 55.37% for $N = 30$, $N = 50$) compared to IDW classic, and keeps the relatively low MAE even in less sample points condition.

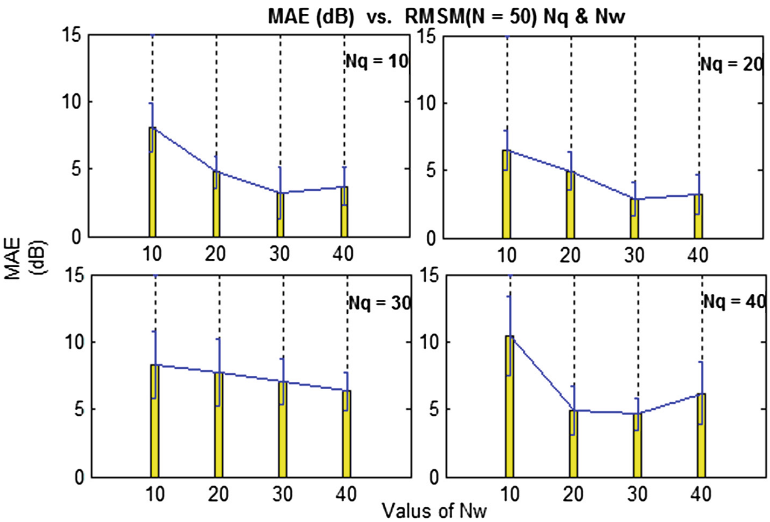

Fig. 5. Performance of RMSM in different values of N_q/N_W

Performance of RMSM itself in different values of N_q/N_W is depicted in Fig. 5. The choosing of these two values is depended on environment surrounding (obstacles, walls etc.), that is, larger N_q means smoothing of complex features. Best case is $N_q = 20$, $N_W = 30$, the MAE is about to 2.85 db in this condition (decreased by 1.96 db compared to IDW Classic), while the standard deviation is about 2.48 db, which indicate the desirable robustness.

4.3 Construction of Radio Environment Map (REM)

Based on the analysis above, this experiment uses the RMSM method for the construction of REM due to its favorable performance. The radio scenario is shown in Fig. 3 also, where six routers (AP1–AP6) work simultaneously. Setting parameters as $N_q = 20$, $N_W = 30$ in measured sample points $N = 50$. Figure 6 presents the REM at different grid points (M) choosing ($M = 1200$ in left sub-diagram, while $M = 30000$ in right one). It is easy to see that, the closer to the router, the larger RSS of the location is, which means the greater radio interference of the position.

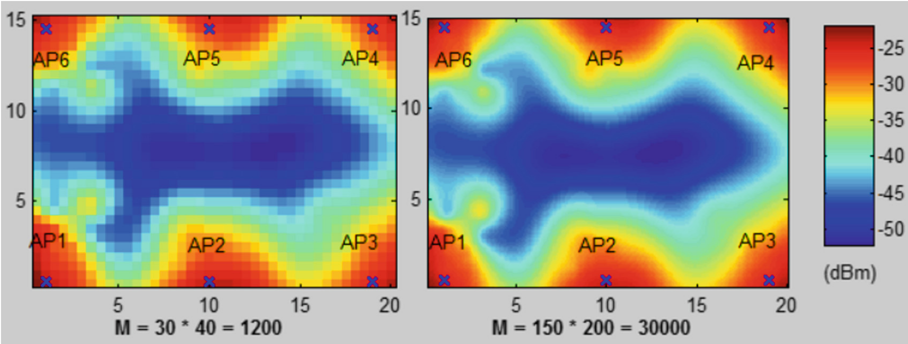

Fig. 6. Schematic diagram of REM

5 Conclusion and Future Work

Through the research on papers or deliverables of Cognitive Radio (CR), Radio Environment Map (REM) and the project FARAMIR, the construction of REM based on Spatial Interpolation is proposed in this paper called RMSM method, which shows the desirable performance in experiments. Future work will focus on environmentally-adaptive RMSM method with radio propagation model and the construction of RSS fingerprint database based on REM.

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