An Interpolation Scheme for Constructing Radio Frequency Maps from Spatial Samples

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ABSTRACT

The development of spectrum measurement infrastructure that can produce real-time geographic maps of spectrum usage is important to the deployment of future wireless systems. Such an infrastructure also provides the basis for creating a spectrum database in support of dynamic spectrum access. We are developing algorithms that can aggregate, classify and geographically map collected RF power measurements so as to support the formation of the spectrum database. A fundamental building block to creating this database is using a collection of spectrum measurements to infer the expected power levels at locations where there was no measurement infrastructure. This project is currently developing a pathloss-based interpolation scheme that can accurately estimate the power levels at locations bounded by four spectrum sensors deployed in a rectangular pattern.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design—*Wireless Communication*

Keywords

HetNet, interpolation, path loss, sensors

1. INTRODUCTION

In future wireless systems, multiple radio access technologies, such as 4G/LTE, WiMAX, WiFi are expected to be deployed in shared spectrum. For efficient spectrum utilization, dynamic spectrum access would require terrain-specific radio maps with information such as location, frequency, transmit power at access points (APs) /base stations (BS), their signal connectivity/ coverage holes, etc. To build such a detailed radio map, radio power from APs/BSs can be measured by randomly distributed mobile devices in the network. A dedicated grid of sensors spanning a large urban area may also be deployed for this purpose, as shown in Fig. 1. The set of sensor measurements can be processed in the logically central database and interpolated over the large area to build the radio map. The use of radio maps can be extended to applications such as spectrum usage policing, network planning and deployment, etc.

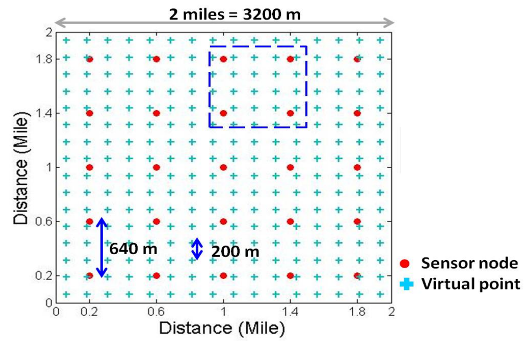


Figure 1: Deployment scenario of sensors and virtual points under consideration

Towards the objective of building a radio map, we focus on a single square of four sensors (red points in Fig. 1) and explore the problem of estimating the radio frequency (RF) power level across a square area bounded by the sensors. We assume initially that there is a single emitter external to this square area and all four sensors scan the same band. However, the method can be scaled and applied to a variety of scenarios.

2. RADIO PATH LOSS MODEL

The received power [dBm] at a sensor placed at an arbitrary position on the terrain is the transmitted power [dBm] plus the path loss (PL) between that point and the transmitter. To form accurate radio maps from sensor data, we exploit the fact that PL can be described using the generic function [1]

$$PL[\text{dB}] = [A + 10\gamma \log_{10}(d/d_r)] + s; d \geq d_r, \qquad (1)$$

where A is an intercept parameter (including antenna gains), γ is the path loss exponent, d is the distance between the emitter and an arbitrary point on the terrain, d_r is a chosen reference distance (chosen here to be 1 m), the bracketed term is the *median path loss* at distance d, and s is the variation about the median path loss at distance d. Also, s is Gauss-distributed with zero mean and standard deviation σ. We assume its variability over the terrain can be described by a spatial correlation function [2]

$$c_{ab} = \sigma^2 \exp(-\frac{d_{ab}}{X_c}). \tag{2}$$

This is the correlation between s_a and s_b at points a and b with separation distance d_{ab}, and X_c is the shadow fading correlation distance. The values of both σ and X_c are environment-specific.

3. PATH LOSS ESTIMATION ALGORITHM

The basis of our approach is founded on the observation that, in practical settings, shadow-fading is highly correlated over small to moderate distances and decorrelates over large distances [3]. Thus, the PL at a particular point is best estimated using the known (or measured) PL values from the set of sensors located nearest to that point. In our study, we propose to use the four sensors surrounding a point of interest, and the resulting local PL model we use is:

$$\begin{aligned} PL_i &= A'' + 10\gamma \log d_i + s_i'', \\ A'' &= A + (s_1 + s_2 + s_3 + s_4)/4, \\ s_i'' &= s_i - (s_1 + s_2 + s_3 + s_4)/4, \end{aligned} \tag{3}$$

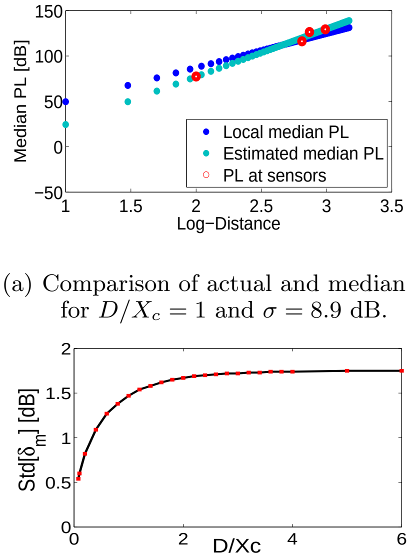
where s_1, s_2, s_3, s_4 are shadow fading values at the four sensors. Note that the four corner values of s'' average to 0, as desired in a model constructed from four sensor measurements. Assuming knowledge of the emitter and sensors, we use the following 3-step algorithm:

1. Least-Square Estimation (LSE) is used to estimate A'' and γ from the four corner samples of PL.
2. Using these estimates, we form the estimated median path loss at each corner and subtract it from the corresponding measured PL, to obtain estimates of s'' at the four corners.
3. A weighted sum of the four estimates of s'' is used to estimate s'' at any point within the square (see the 'virtual points' in Fig.1.)

In [4], the weights were chosen (from intuitive reasoning) to be inverse powers of the sensor-to-virtual-point distances, scaled so as to sum to 1. In our current work, we are exploiting the use of multivariate Gaussian distributions to obtain theoretically optimal weights; though not obtainable if the correlations among s-values are unknown, these solutions will help to improve our intuition on weight selection.

4. EVALUATION

The proposed path loss estimation algorithm is evaluated in two steps: (1) error due to the imperfect estimation of A'' and γ, and (2) error due to the imperfect estimation of the measured s''-values. In our work, we study the two errors separately, for the purpose of better understanding.



(a) Comparison of actual and median PL for $D/X_c = 1$ and $\sigma = 8.9$ dB.

(b) Median PL error, δ_m, for $\sigma = 8.9$dB.

Figure 2: Evaluation of path loss estimation

To evaluate the effect of imperfect estimation of A'' and γ, we compare actual and estimated median PL values as a function of the distance d_i between emitter and receiver. Results shows that both the values match as long as d_i is within the range of minimum and maximum distances from the emitter to the sensors. Fig. 2(a) is a snapshot of the comparison for a particular instantiation of $[s_1, s_2, s_3, s_4]$. Furthermore, the estimation error for median PL, δ_m, is characterized as a function of D/X_c, where D is the side of the square, and D/X_c is a measure of the sensor density. As shown in Fig. 2(b), the asymptotic RMS error of δ_m (which scales with σ) is only 1.8 dB for high value of $\sigma = 8.9$ dB used here.

Going forward, we are currently in a phase of developing algorithm to estimate s'' and quantifying its error statistics over the area inside the square. The errors in median PL and s'' will be combined together to get the overall accuracy for radio mapping. Also, we have studied the impact of location for emitters outside the square; a logical extension of our work will be to study the case of emitters inside the square.

5. REFERENCES

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