A Software Tool for Coverage Planning through Different Applications of Optimal Spatial Interpolation

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***Abstract*—In the recent years there has been an effort for the wireless systems to become more efficient in terms of power consumption and coverage planning. One aspect of this effort was the proposal of using spatial estimation approaches, that exploit the spatial correlation of the shadowing and received power, to improve propagation prediction. In this demonstration, we present a software tool that implements these spatial estimation approaches and can be a part of a general network planning tool. Among others, it can provide a valuable insight on which of the approaches provide better results in a given situation, or information about the needed drive test measurements. Our demonstration is based on real, high spatially granular measurement data in various environments and frequencies, but it can be easily extended though to real-time data acquisition from portable spectrum measurement devices, smartphones or drive test measurements.**

I. Introduction & Motivation

In recent years, the need for wireless systems that are able to utilize schemes and techniques from the areas of Dynamic Spectrum Access (DSA), secondary use of spectrum resources, small cell networks and green communications, led to an increased interest in improving the understanding of the characteristics of the radio environment. By better understanding the propagation environment, the wireless systems can become more efficient in terms of power consumption and coverage planning. The main propagation phenomena in the wireless signal transmission are the deterministic distance-based losses, the small scale fading due to multipath (that is modeled in worst case as a Rayleigh random variable) and the shadowing that corresponds to the uncertainty of the received power in a certain location. Shadow fading is modeled as a normal distributed random variable in log scale [1]. A recent approach to improve the radio propagation estimation is to exploit the spatial structure of the shadowing or the received power, over the coverage area [2]–[4]. This improvement can be achieved by the use of spatial interpolation schemes and by applying such estimation methods to both drive test and mobile phone originating (MDT) data.

In this demonstration we showcase a tool that provides a comprehensive analysis of two approaches in which the spatial statistics are used to decrease the received power uncertainties. Our tool employes the optimal linear predictor, i.e. *kriging*, on the shadowing field and on the received power. This allows a detailed comparison between the two approaches. Our demonstration allows the attendees to use different propagation models or provide data in terms of a ”generalised shadowing” implementation (where the large scale predictions come from ray-tracing or other operation planning tools). It also can be easily extended to real-time data acquisition from smartphones or drive test measurements. Our implementation can be used either as a stand-alone propagation estimator or in the core of a network planning tool.

In the following sections we first give a short description of our software tool and then we give an outline of the proposed demonstration.

II. Background

In this section we present in brief the main concepts used in our demonstration. We also introduce the different approaches used for estimating the received power and explain shortly the statistical tools used in each case.

The basic approach of estimating the received power in a certain location by using measurement based or theoretical propagation models, does not consider the vastly different surroundings that two locations with the same transmitter-receiver separation could have. This approach needs an appropriate path loss model with some measurement points in various locations. This method takes into account the propagation environment through the path loss exponent, but treats shadowing as a random variable that has a common distribution, without taking advantage of the spatial correlation of the signal [1].

The spatial correlations can be exploited with various spatial interpolation methods for a more precise estimation of the shadowing. Both of the following approaches presented in our work, use the kriging as the spatial interpolation method. The interested user should note though that there are also other spatial interpolation methods that can be used, but kriging is in general the optimal. In particular, kriging is the optimal linear predictor of a spatially correlated random field, given the correlation of the field. The correlation can be estimated from various spatial-statistical tools such as the correlogram and the covariogram. In our analysis, we use the variogram because of its better statistical characteristics [5]. The variogram is given by

$$\gamma(x,y) = \frac{1}{2}\,\mathrm{Var}(Z(x) - Z(y)), \quad (1)$$

where Var is the variance, $Z(*)$ is the random field and x, y are two locations.

The first approach that takes into account the spatial statistics, exploits the spatial correlation of the shadowing. In particular, the measurement data with the small scale fading averaged-out during the measurement itself, the location of the transmitter and the path loss model, are used to extract the shadowing field in the area of interest. The shadowing field is the residuals of a path loss model that is fitted to the measured received power data. Secondly, the experimental semivariogram is calculated and fitted to theoretical models that provide estimations of the parameters of the variogram. This step, provides a marginal distribution, that also utilizes the spatial correlations of the field, as parameters of the variogram. Finally, the kriging is employed to estimate the shadowing field. More details about this approach can be found in [5]–[7].

The second approach that enables the use of spatial statistics, is applying kriging on the measured received power. In this approach there is no need of fitting the data to a path loss model and thus no shadowing extraction is taking place. This lowers the computational burden, since the fitting used in the first approach has to be repeated when the data-set is changing or is enriched with new measurement points. Another point of interest is that there is no need for information on the location of the transmitter. This becomes really important in systems with multiple transmitters covering the same area, since the signal received in a location can be sent from different transmitters.

Main difference between the above mentioned approaches is the gaussianity of the input data to the kriging process. In the first approach, by extracting and using shadow field, we create a more Gaussian field (than the received power in the second approach). This can be done though only in the expense of using the location information of the transmitter and the computational cost for fitting. Our work in [7] illustrated that there is a trade off between the approaches that consider the spatial correlations, on the outliers of the received power estimation, the number of measurement points used as training in the spatial interpolation and the overhead of computations. This trade off along with the above mentioned approaches, analysis and comparisons are the main concepts presented in our tool.

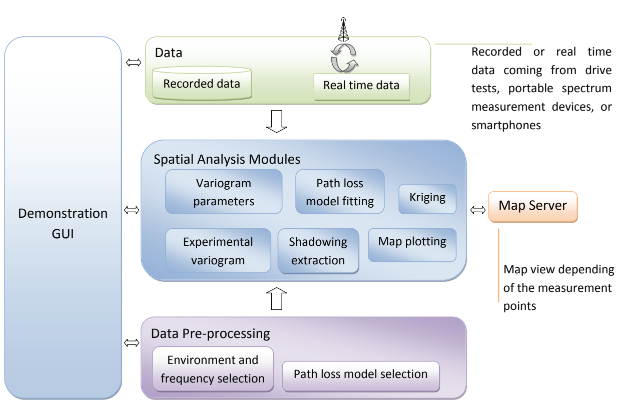


Fig. 1. System Architecture

III. Implementation

The high level architecture of the software tool is illustrated in Fig. 1. Recorded or real time data can be loaded or read to/from the software. After the selection of the data is done, the environment and frequency information must be given either manually (in case of real time data) or through the loaded file. Our prototype is based on data-sets gathered during two high spatially granular measurement campaigns conducted in two different environments, an urban and a suburban one, and at two different frequencies, namely the $485\,\mathrm{MHz}$ and $2600\,\mathrm{MHz}$ that were presented in [6] and [8]. Each data-set is comprised of three columns, providing the Longitude, Latitude pairs and the respective measured power. The number of rows represent the number of measurement points in the data-set. In addition to the 3 column tabular data, the recorded files incorporate some metadata used in the analysis. An example of these metadata are the frequency band and the type of environment, where the measurements were conducted.

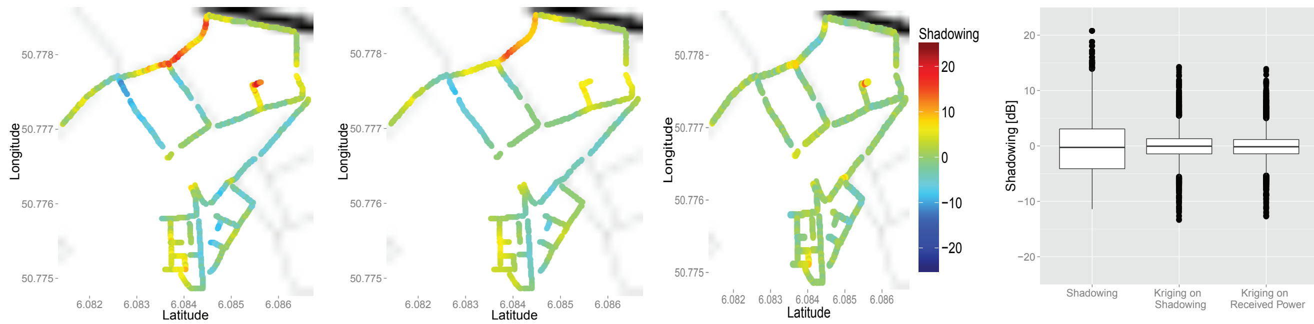
After loading is done, the data are processed by different spatial statistical analysis modules. In the first step of analysis, the marginal distributions of the received power and the extracted shadowing field are calculated and depicted as histograms with density plots. Moreover, a map with the locations of the measurement points and the experimental and exponential fitting of the semivariogram are illustrated. The attendees can interact with the prototype by adding their own path loss model or use one of the various models provided. This allows the easier comparison between the shadow fields calculated from different path loss models, for different frequencies and environments.

Prediction procedure

As the spatial estimation procedure is one of the main points of our implementation, we provide here a more detailed description of it.

In order to evaluate the kriging, we divide the measurement points into *training points* and *verification points*. The training points are chosen randomly out of all the measured points, so as to provide unbiased results.

For the kriging on the shadowing field approach, we use these training points to fit the chosen from the user propagation model and then extract the shadowing for these points. After the shadowing extraction we calculate the variogram and its parameters. This information is used to train the kriging function, so as to interpolate the field at the verification points.



(a) Measured shadowing (b) Kriging on shadowing (c) Kriging on received power (d) Boxplot

Fig. 2. Shadowing extracted from (a) measurements, (b) kriging on shadowing and (c) kriging on received power. (d) depicts the comparison between the three approaches

For the case of the kriging on the received power, we use these training points to calculate the variogram and its parameters, without fitting and extracting the shadowing field. Then the spatial estimation algorithm is trained and run for the interpolation on the verification points.

Our prototype in both approaches, calculates and plots the estimation error and repeats the estimations to provide the error distribution. The attendees can choose one of the approaches or both to be evaluated. In addition, they can change the number of iterations that the kriging takes place, so as to provide the boxplots. Finally, they can change the number of training points used, so as to investigate the impact of the different number of measurement points in the procedure.

IV. Demonstration Outline

Here we present our proposed flow of the demonstration. First the attendee will be able to choose a recorded data-set or to provide their data-set. Next, the spatial analysis of the shadowing will follow. During this analysis, the user will be introduced to the main characteristics of the spatial statistics such as the experimental and the theoretical variogram and its main parameters [5], [9]. Moreover, the user will be able to choose between the already available path loss models or to provide his/her own propagation model. At this point the differences on the extracted marginal distribution of shadowing and the robustness of the variogram will be shown through the plots presented on the GUI. Further, the kriging on the shadowing field or on the received power will be analyzed and examined in respect to the estimation error.

In the last part of our demonstration, the comparison of the kriging analysis on the received powers and the extracted shadowing will take place. The two proposed analysis will be compared in the form of boxplots that depict the distribution of the shadowing for the same number of training points (Fig 2). As above the users can interact with the prototype in a number of ways such as by changing the used path loss model, area and frequency, or the number of iterations of the spatial interpolation and the number of training points. This will enable the attendees to develop deep understanding of the tradeoffs involved in the coverage prediction problem in terms of the amount of data available, complexity of the propagation environment, and the model used for obtaining the final predictions.

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