Automated Coverage Hole Detection for Cellular Networks Using Radio Environment Maps

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***Abstract*—The existence of coverage holes in cellular networks is a common problem for mobile operators. Traditionally, the cellular coverage is computed using sophisticated planning tools, and then optimized through drive tests. With the drive tests information, the operators detect the poorly covered areas and take actions to eliminate them. The introduction of self-organized or "cognitive" techniques, would allow the operators to maximize the network's information obtained through drive tests or reported by the mobile users. In this paper we propose the use of spatial Bayesian geo-statistics to build a Radio Environment Map (REM) for real coverage hole detection purposes. Results show that the number of pixels forming the coverage holes, as well as the probability of detecting them, can be significantly increased with the use of REMs, compared to the case where only network measurements are used.**

***Keywords*—Coverage hole detection, minimization of drive tests, spatial information exploitation, REM.**

I. Introduction

When deploying a Radio Access Technology (RAT), coverage planning is a complex task for operators since they need to consider multiple and correlated network parameters as well as environmental conditions that are out of their control. Completely avoiding the existence of coverage holes in cellular networks during the planing phase is almost impossible and therefore, coverage optimization processes are usually required during the operational phase. Traditionally, cellular coverage optimization is performed through drive tests, which consist of geographically measuring different network coverage metrics with a motor vehicle equipped with mobile radio measurement facilities. The collected network measurements need to be processed by radio experts for network coverage optimization, e.g. by tuning network parameters such as transmission power, antenna orientations and tilts, etc.

The use of drive tests imply large Operational Expenditure (OPEX) and delays in detecting the problems, and they cannot offer a complete and reliable picture of the network situation. Additionally, they tend to be limited to roads and other regions accessible by motor vehicles, and are not helpful in detecting coverage problems inside buildings. They are also an undesirable source of pollution. These reasons drive operators to make the most of the information collected through the drive tests, and to minimize the use of them. Therefore, since Release 9, the 3rd Generation Partnership Project (3GPP), the key standardization body for cellular networks, has been working on the optimization of drive tests [1] and since Release 10, a feature called as Minimization of Drive Tests (MDT) has been included in the standard, both for 3G (including also High Speed Packet Access (HSPA) and Long Term Evolution (LTE) [2], [3]). The key idea of the MDT is that the network operator can request the User Equipments (UEs) to perform and report specific radio and Quality of Service (QoS) measurements associated to the UE location for troubleshooting and optimization purposes. Also, automation of network operations and management, including network optimization, is an important topic currently studied in 3GPP, in the framework of Self-Organized Networks (SONs), comprising self-optimization, self-configuration and self-healing operations. The main targets of SON are to decrease expenses, increase the network autonomy and achieve an automatic, near optimal network performance in terms of coverage, resource exploitation, energy efficiency and load balancing, to name a few common criteria [4].

In this paper, we introduce an automated coverage hole detection approach that could be the first step of a coverage self-optimization process. The proposed approach is based on a cognitive tool that provides location awareness [5]: Radio Environment Maps (REMs). The REM concept was first introduced as an integrated database for Cognitive Radio (CR) systems that are based on opportunistic spectrum access, such as TV white spaces [6]. In our work, we consider a broader view of the concept of REM, which introduces the ideas of Interference Cartography (IC) [7]–[9], where the REM is constructed through *spatial interpolation* of geo-located measurements (i.e. drive test measurements, geo-located network statistics and UE reports in the context of cellular radio networks). The main difference of this IC approach with regards to the initially proposed concept of REM is that IC constructs the cartography based on measurements partially spanning the area of interest, spatial interpolation techniques and additional measurement request mechanisms. The IC approach for REM has been shown to be an effective method for wireless network optimization in [10]–[12]. For the spatial interpolation, we use the Bayesian kriging technique [13], which exploits all the available information regarding the network performance.

Without exaggeration, we can say that coverage is the most important and the highest-priority target that has to be achieved by cellular operators. Without coverage provisioning, it is meaningless to talk about service, or QoS provisioning. Therefore, cellular coverage prediction and enhancement remains as a basic and prevailing area of research and investigation in wireless communications. To the best of our knowledge, the problem of automated coverage hole detection based on spatial statistical processing of geo-located measurements has only been treated for sensor networks but not for cellular networks, until the present line of work. Considering that sensor networks and cellular networks differ to a great extent in aspects such as coverage definition/requirements and measurement collection/request mechanisms, we can claim that the present line of work is the first to investigate automated coverage prediction in cellular networks.

The work we present in this paper is a continuation of the work presented in [11]. Differently from [11], in this paper we give a more realistic evaluation of the REM-based coverage hole prediction, since in the present analysis, a more realistic coverage hole definition is considered. In [11], a non-covered pixel was considered as a coverage hole, independently from the fact that its neighboring pixels were covered or not. However, in reality, a coverage hole frequently consists of *neighboring* uncovered pixels. Thus, a set of neighboring N pixels constitute a single coverage hole, but not N separate coverage holes. Therefore, in this paper, we have adopted the notion of neighboring pixels in defining a coverage hole and enhanced our performance analysis with respect to the pixel-based analysis in [11]. Our aim is to measure the gains introduced by the use of REMs in coverage hole prediction where coverage hole is defined in a more realistic sense as described above. The coverage measurement data used in this work can be considered as real measurements, since they are obtained from a very accurate planning tool that uses a ray-tracing propagation model.

The rest of this paper is organized as follows. Section II describes the considered scenario, including network measurements and related parameters, as well as the proposed methods for coverage hole detection and evaluation. Section III presents the performance of the spatial interpolation process and of the proposed coverage hole detection method. Finally, Section IV summarizes the main conclusions.

II. Scenario and Methodology

In this section we present the considered scenario, the parameters used to evaluate the proposed coverage hole detection algorithm, the evaluation methodology and the indicators defined for evaluation purposes.

A. Scenario, Measurements and Parameters

The analysis is performed over geo-located Received Signal Code Power (RSCP) values from a 3G network deployed in a dense urban area in the south of Paris, France. The used RSCP values are obtained with a reliable planning tool with highly accurate propagation models, which is commonly used for operational network planning [14]. For the calibration of the propagation model, the environmental conditions, i.e. terrain profile and buildings, were considered and they were also validated through repeated drive tests. Therefore, it can be assumed that this RSCP data represents very closely the "ground-truth" in the given area. In what follows we refer to the map obtained from this RSCP data as the *real coverage map*. It is worth noting that the proposed approach is not limited to 3G, but is a generic one which can be applied to any radio access technology. For example, by using the method proposed in [15], to transform the RSCP values to Reference Signal Received Power (RSRP) values, a similar coverage hole detection analysis could be carried out for LTE with a change in the value of the coverage threshold only.

The above-mentioned real coverage map, presented in Figure 1, has a grid granularity of $25\ \mathrm{m} \times 25\ \mathrm{m}$. In the remainder of this paper we refer to this grid area as a pixel. We define a minimum RSCP coverage threshold of -123 dBm and those pixels where the received RSCP is below this threshold are considered to be uncovered. Figure 2 represents the binary map of the real coverage map, where the uncovered pixels are represented in gray and the covered pixels are represented in white. Another important parameter to define is the minimum number of neighboring uncovered pixels which an operator considers as an area with coverage problems where some corrective actions have to be taken. Considering the environment (urban) and the grid size ($25\ \mathrm{m} \times 25\ \mathrm{m}$), we use a typical value of 4 neighboring pixels and we refer to this area as a *coverage hole*.

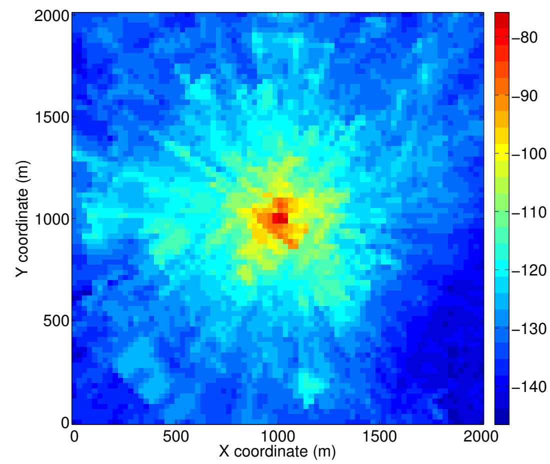


Fig. 1. RSCP coverage map measured in dBm used as the ground-truth.

In dealing with coverage holes over a geographical zone of operation, usually a practical approach taken by operators is to prioritize (groups of) coverage holes rather than handling all the coverage holes at once. Therefore, those coverage holes that have the potential to have a larger (negative) impact on operator's prioritized targets are dealt with higher priority than the others. In this work, we adopt a similar *local* approach and consider a typical prioritization aspect: we focus on the *largest* coverage hole (i.e. coverage hole with the largest geographical area). Therefore, the proposed analysis is carried out on the neighboring area around the largest coverage hole, as can be seen Figure 2.

Operators already have an idea on such neighboring areas thanks to traditional network diagnostics based on human-expert processing of alarm tickets, customer complaints and routine drive-test measurements collected from the neighborhood. When such an area is suspected to have a coverage hole, the traditional method to deal with this situation is to send out drive test equipment and experts to that area to perform detailed/thorough drive tests and analyze the obtained measurements in order to: (1) detect the presence and (2) accurately identify the shape of the coverage hole for further (corrective) actions.

The REM-based analysis proposed in this paper is meant to replace this phase of detailed/local drive test measurement collection and analysis, by using geo-located measurements reported by UEs present around the coverage hole. Although UEs cannot report *immediate* measurements when they are *within* a coverage hole, mechanisms such as *logged* Radio Link Failure (RLF) reporting exist in the MDT framework, which

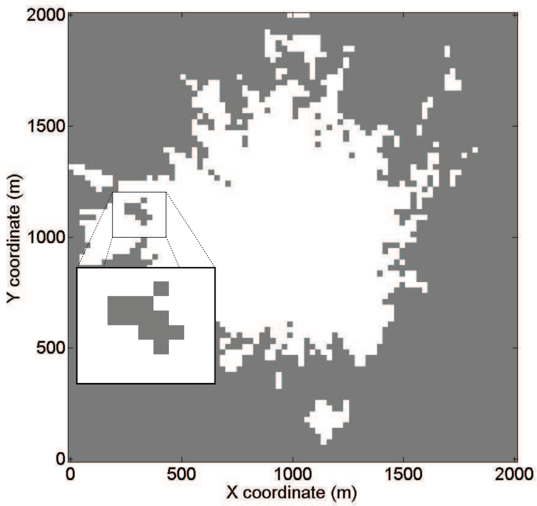


Fig. 2. Coverage area corresponding to the RSCP map shown in Fig. 1.

allow the UEs to log the measurements when they lose the network connection and report the logged measurements as soon as they get reconnected [2]. Furthermore, measurements could be requested to UEs inside the covergae hole, attached to other technologies. In this way, valuable geo-located data related to the coverage loss can be used by the network operator. Thus, instead of performing a second round of (local and dedicated) drive test measurements and manually processing/analyzing those measurements, the operator constructs a remote representation of the local network coverage (i.e. REM) over the suspected area, hence minimizing the overall number of drive tests and the expenses/delays they imply.

In Figure 3(a), we can see the binary map of the larger coverage hole found in the real coverage map, and zoomed in Figure 2. Figure 3(b) represents the operator's (partial) view on the zoomed area: black pixels show locations where there are no measurements.

The automated construction of REM uses spatial statistics, namely Bayesian kriging, to have a realistic representation of the ground-truth. Application of Bayesian kriging to coverage REM construction is described in [11], where a preliminary performance analysis on pixel-level coverage is also given. The entity which carries out the REM construction is a software framework called as the REM manager [16]. The REM manager is located at the Operations and Maintenance Centre (OMC) and it is in charge of collecting and analyzing the UE reports, the collected measurements, etc. and to perform the coverage prediction.

B. Proposed Methodology and Evaluation Method

We assume that, based on UE reports, network measurements used for common Radio Resource Management (RRM) purposes, drive test, users complaints, etc., the REM manager can identify areas with coverage problems. Once the operator detects an area with a potential coverage hole, it applies the coverage hole detection approach, which consists in the following steps:

1) The REM manager verifies whether it has enough network information, i.e. a required percentage of pixels, p, with available measurements for performing the interpolation process. If not, the REM manager sends a measurement request to those UEs around the problematic area until it collects measurements on p pixels. Here, it is worth pointing out that we consider a static scenario, and thus there are not time constraints. In any case, the delay in waiting for the required UE measurements will always be lower than the required time to perform drive tests. Therefore, we can affirm that the delays introduced by the proposed coverage hole detection methodology are not significant in comparison with the conventional methods. Figure 3(b) represents an example of a real information situation for the area under study, for the case of $p = 50\%$, where the squares in color represent real measurements and the black squares represent those pixels where measurements are not available and the interpolation is to be performed.
2) Once the minimum required measurements are gathered, the REM manager performs the Bayesian interpolation [13] to estimate the RSCP values in those points where it lacks information. Examples of Bayesian interpolation for REM construction can be found in [10], [11]. Finally, the REM manager can construct the REM by overlapping the available real measurements (Figure 3(b)) and the ones resulting from the interpolation process. When the threshold is applied, it results, for instance, in a map as the one presented in Figure 3(c).

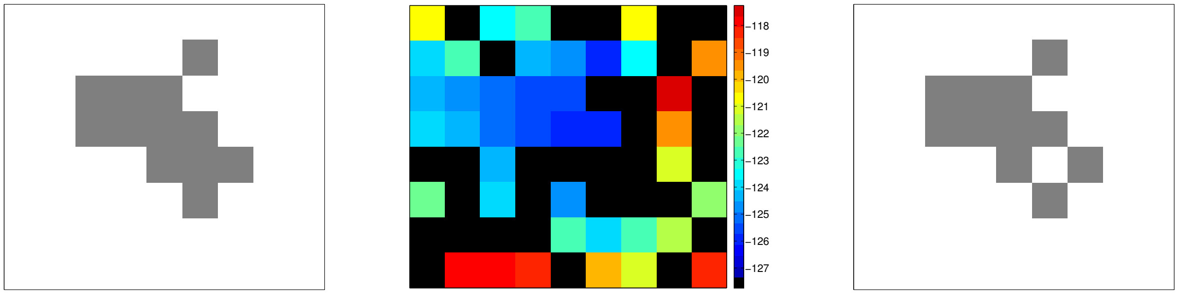
An important aspect to highlight is that the proposed methodology does not imply any modification in the existing network entities. The new functionalities, i.e. the REM manager, is a software-based approach to be introduced at the OMC level [16]. This makes upgrading existing networks, to benefit from the proposed methodology, both very straightforward and cost-effective.

For the evaluation process we define, at a pixel level, the average interpolation error. It measures the average amount of pixels incorrectly estimated in the interpolation process. This average consists of the false alarm and misdetection probabilities. On the one hand, the false alarm probability measures how many pixels are estimated to have a RSCP below the threshold when in reality it is above the threshold. On the other hand, the misdetection probability measures how many pixels are estimated to have a RSCP above the threshold when the real measurement is below or equal to the RSCP threshold [11].

We then present the results obtained when the coverage hole concept, of N uncovered neighboring pixels, is considered in the evaluation process. First, we measure the gain in the detection probability of the pixels forming the coverage holes. Second, we estimate the probability of detecting the coverage hole. This probability is measured in such a way that if more than a given percentage of the pixels, c, belonging to the coverage hole are correctly identified, then we assume that the coverage hole has been detected, otherwise, we consider that the detection procedure has failed.

III. Evaluation Results

In this section we present the evaluation results for our methodology from two perspectives. On the one hand, we evaluate the accuracy of the interpolation process, and on



(a) Larger covergae hole map (b) Available measurements for interpolation (c) Resulting map after interpolation

Fig. 3. Real and interpolated ground-truth maps.

the other hand, we evaluate the effectiveness of the proposed methodology for the real coverage hole detection. We focus on the largest detected coverage hole in the binary coverage map for the statistical evaluation. Statistics are computed for 1000 snapshots, from where on the results converge. Results presented in this section have been estimated for different percentages of available measurements, $p = \{50, 60, 70, 80, 90\}\%$, used in the interpolation process (see Figure 3(b)). Translating p into required measurements per square meter, results in $q = \{0.08, 0.096, 0.112, 0.128, 0.144\}$ UE's RSCP reports per square meter, which is a very small amount of measurements due to the static nature of the problem and the size of the grid. As future work, we would like to consider in the evaluation process the patterns of the density of population as well as the uncertainty on the measurement locations.

A. Pixel Level Detection Performance

Results presented in this section evaluate the interpolation reliability on a pixel level. Figure 4 represents the average interpolation error. This average error is broken down into false alarm and misdetection probabilities. Results presented in Figure 4 show that the interpolation process performs well, even for low amount of available measurements, i.e. $p = 50\%$, with an average error around 10%. As expected, as the amount of available measurements for the interpolation process increases, its accuracy improves and therefore, the average error decreases, reaching a value of around 2% when $p = 90\%$.

B. Coverage Hole Detection

In this section we evaluate the accuracy of the proposed pixel-wise methodology for realistic coverage hole detection. In the following figures we use the acronym CH to refer to Coverage Hole. In Figure 5 we find:

- Light blue bars representing the average percentage of measured pixels, which is equal to the number of coverage hole pixels measured by the operator, divided by the number of pixels forming the coverage hole.
- Dark blue bars representing the average percentage of detected pixels with REM which is equal to the number of coverage hole pixels measured by the operator plus those (uncovered) pixels correctly estimated by the REM, divided by the number of pixels forming the coverage hole

These average percentage values are obtained over a statistically significant number of independent "snapshots" where

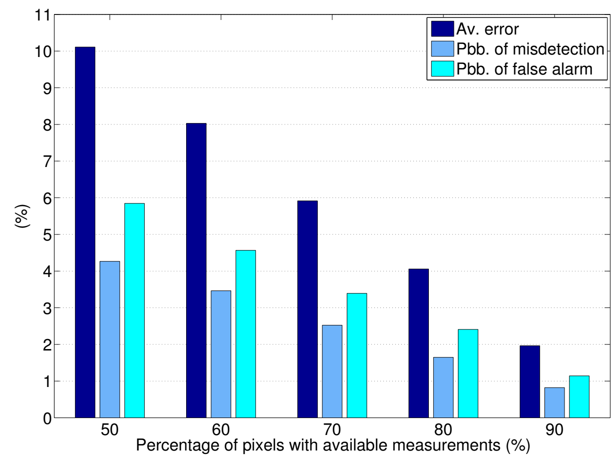


Fig. 4. The average error, false alarm, and misdetection probabilities in the interpolation process.

at each snapshot, the available measurement pixels are uniformly chosen. It is due to this uniform distribution that the average percentage of measured pixel values (light blue bars) correspond exactly to the percentage of available measurement (horizontal axis) values in Figure 5. It can be observed that, as the number p of measurements available for the interpolation process increases, the average number of the coverage hole pixels known by the operator also increases. Figure 5 shows that the REM introduces a 20% of additional knowledge on the coverage hole pixels to the network measurements, when $p = 50\%$. The knowledge on the coverage hole pixels reaches an approximate value of 94% for $p = 90\%$ when REM is used.

Figure 6 represents the probability of detecting the coverage hole for $c = \{50, 70, 90\}\%$ when the REM is used. It can be observed that, when half of the coverage hole pixels are required to be known, $c = 50\%$, the coverage hole is detected in more than 92% of the cases, even for low amounts of available measurements, i.e. $p = 50\%$. Here it is worth highlighting that for the highly demanding case of $c = 90\%$, the detection probability increases up to 95% for $p = 90\%$.

Comparing the probability of detecting a coverage hole for the cases when the REM is constructed and when only network measurements are used, we can conclude that the detection probability significantly increases with the use of REM. Figure 7 depicts the coverage hole detection probability for both cases for the highly demanding requirement of coverage hole detected pixels $c = 90\%$. We see that for a

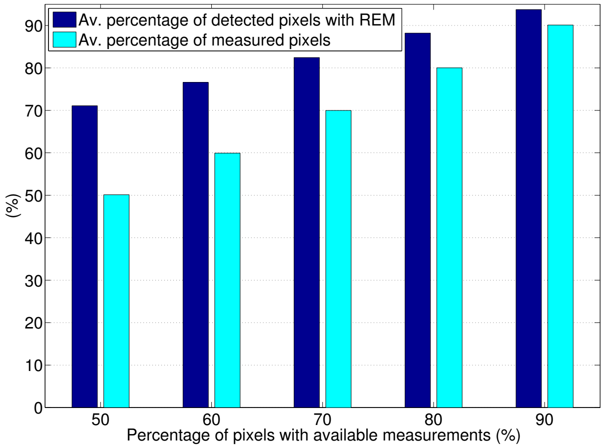


Fig. 5. Average known coverage hole pixels for only network measurements and REM.

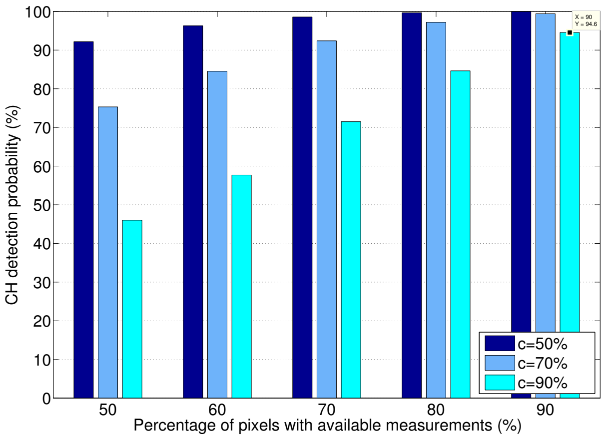


Fig. 6. Average probability of coverage hole detection as a function of c (see end of Section II) for different percentages p of pixels for which measurements are available, when using REM.

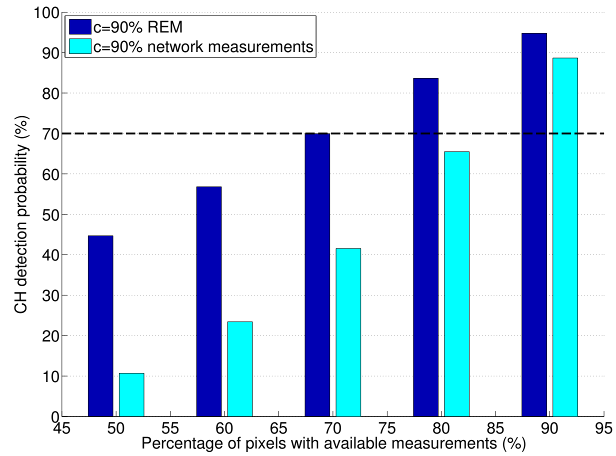


Fig. 7. Average probability of coverage hole detection for only network measurements and REM.

low amount of measurements, $p = 50\%$, the coverage hole detection probability increases 35% when REM is used and for high amount of available measurements, $p = 90\%$, the coverage hole detection probability still increases by about 6% with the REM. Furthermore, a very striking fact evidenced by Figure 7, and highlighted by the dashed black line is that, for achieving a 70% coverage hole detection probability, the REM requires 70% of available measurements, whereas without the REM, we need more than 80% of measurements to achieve the same detection probability. Thus, REM saves more than 10% of measurements for the same performance level of coverage hole detection.

IV. Conclusion

In this paper we have evaluated the improvements obtained when introducing REMs for coverage hole detection in cellular networks. The REM we propose to implement is built through spatial Bayesian predictions. The presented results were obtained for realistic coverage data, computed through an accurate operator planning tool. Analyzing the obtained results we can affirm that the proposed solution allows a remote and automated cellular coverage detection, that enhances the accuracy of the coverage hole detection with a limited required number of measurements. The next step in the troubleshooting process, once the coverage hole detection is performed, is to carry out the optimization of parameter settings, such as transmission power, antenna configurations, etc., to solve the coverage problem. In the parameter optimization phase, the information offered by the REM can also be exploited in order to enrich the system knowledge and enhance the optimization efficiency. Using REM information for network parameter optimization is one of the key research areas we are pursuing in future work.

The spatial estimation techniques used in this work have also further applications beyond estimation of received power values and other signal domain characteristics. For example, by carrying out measurements in the uplink band, similar techniques could be used to more precisely map the density of users in different regions covered by the operator's network. Having such information in a finer level of detail than allowed by existing approaches would be very useful as a foundation of next generation network planning tools, for example. The developed Bayesian reasoning framework forms a very flexible foundation for such applications, as it allows to take various uncertainties, such as localization errors by devices carrying out the measurements in a natural manner. Exploring these issues in more detail and through experimental prototypes forms a core part of our ongoing research.

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