

Estimation of Local Coverage Areas Based on Detected Objects

Jorge Bernad
University of Zaragoza
Zaragoza, Spain
jbernad@unizar.es

Carlos Bobed
University of Zaragoza
Zaragoza, Spain
cbobed@unizar.es

Eduardo Mena
University of Zaragoza
Zaragoza, Spain
emena@unizar.es

ABSTRACT

We face the problem of estimating the real coverage area of a certain (mobile or static) object in a wireless scenario by considering as input data just the location of the devices that can communicate with that object. We propose and evaluate different algorithms to show that estimating the real coverage area of an object without assuming a disk of fixed radius, is not only possible but also simple and efficient.

CCS CONCEPTS

• Information systems → Mobile information processing systems; Location based services; Evaluation of retrieval results;

KEYWORDS

Coverage Area Estimation, Location Based Services

1 INTRODUCTION

Selecting the best places from which to scan a certain geographic area is still an open problem, and so it is knowing the actual area that each object is able to scan from its current location. Both are needed to ensure that a given interesting area is completely monitored by a set of active (mobile) monitors. Some approaches [3] assume a simplified modeling of the range area of objects (a disk of a certain radius centered on the location of objects) while others try to estimate it by using extra geographic information and defining complex physical models of the behavior of wireless signals [1, 2]. Unfortunately, these models do not fit well in any real situation, and/or require information that is not always available.

In this paper we advocate taking as basis only simple but solid input data to estimate the coverage area of an object: the location of objects that it really detects from its current location at each time. We propose different algorithms based on these input data that estimate the real coverage area of an object and show their feasibility, accuracy, and efficiency, even in the absence of any further information.

As a motivating example, let us suppose that a user wants to know which of his/her friends are inside a certain area in the old part of the city where they use to go. In Figure 1 we can see the interesting area in purple, the device of a person who is walking down the street (represented by the red dot), and its ideal (not considering obstacles) and real communication ranges displayed in pink and green, respectively. Notice that by considering the ideal coverage area (in pink) the red device is supposed to intersect about 25% of the interesting area; however, due to the narrow streets its real coverage area is much smaller.

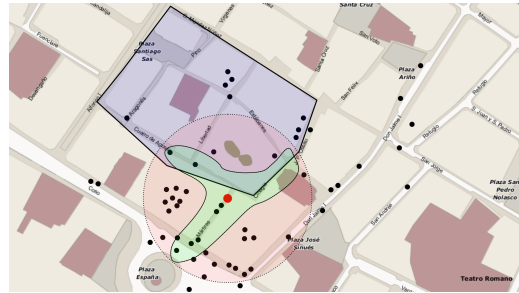


Figure 1: Estimated vs. real coverage area from the red device.

Relying on the objects in the scenario that a given object detects from its location at each time seems a good starting point to estimate its real coverage area, task that should be performed quickly, with a good accuracy, and making no assumptions about objects or scenarios.

2 COVERAGE AREA ESTIMATION METHODS

In this section, we explain two methods to obtain a coverage area estimator based on an adaptive disk and the convex hull of a set of points; as such methods cannot detect *holes* in the real coverage area, we introduce two extra methods based on a polar grid and the Delaunay triangulation.

Adaptive Disk Method. This estimator is a variation of the disk model, broadly adopted [3], where the coverage area is assumed to be a disk of a given radius r . This estimator returns a disk whose radius is the distance to the furthest visible object in the scenario.

Convex Hull Method. This method is based on the recursive subdivision of the triangulation given by the convex hull of the positions of the detected objects (Figure 2.a). The subdivision criteria depends on a value α_i calculated for each candidate triangle, which in turns depends on a value A that represents the size of an “empty big area”. Such A value is obtained detecting area outlier triangles.

Polar Grid Method. This method is based on a polar grid (a grid in polar coordinates of the points in the plane). It is determined by a maximum distance ρ , and the number of divisions r and s for the module and the angle. Intuitively, the method avoids the *holes* in the real coverage area by means of the propagation (with mitigation) of the witnesses’ votes towards the center of the grid (Figure 2.b).

Delaunay Triangulation Method. Finally, this method is based on obtaining the *Delaunay triangulation* of the detected objects. After having the triangulation, this method filters out big empty areas exploiting the fact that the Delaunay triangulation maximizes the area of the triangles regard to its perimeter. In Figure 3.a, we can see the Delaunay triangulation of a set of points, and in Figure 3.b, how it matches against the real coverage area.

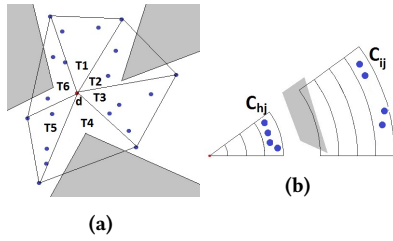


Figure 2: a) Convex hull, and b) Polar Grid methods.

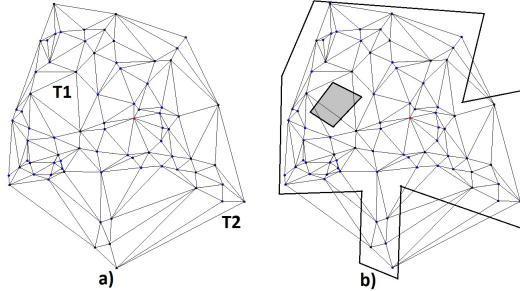


Figure 3: a) Delaunay triangulation; b) vs. real coverage area.

3 EXPERIMENTAL EVALUATION

In this section, we present the evaluation of the different coverage area estimators using synthetic and real scenarios.

Synthetic scenarios. We have built a set of 1,000 synthetic scenarios where the coverage area is represented by a disk of 300 distance units with a variability of $\pm 5\%$ in different directions. Each scenario contains a set of detected objects (ranging from 2–1,000) randomly placed within the coverage area, and holes up to a 90%. Besides, we adopt the 80/20 split often used in machine learning to propose and validate a mixed algorithm depending on the number of the objects detected¹.

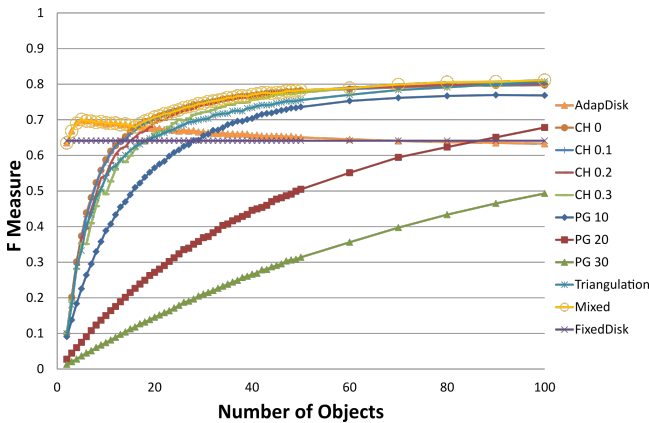


Figure 4: Algorithms accuracy for up to 100 objects.

In Figure 4, we can see the different average F-Measures obtained by the different estimators on the 200 validation scenarios. The

¹The datasets containing all scenarios and objects, and all the evaluation results are available at <http://sid.cps.unizar.es/SHERLOCK/coverageAreas/>

mixed algorithm selects the method that behaves the best in the other 800 scenarios for a given amount of detected objects. Performance tests (not included here due to space limitation but available at our project’s webpage) show that algorithms are efficient enough so as to be executed continually.

Real scenario. We have also used a real dataset of the signal strength of the GoogleWiFi measured in a 12 km² zone in Mountain View [2]. The dataset contains the GPS coordinates of a location, an identifier of an access point that covers such a location, and the signal strength measured in decibels.

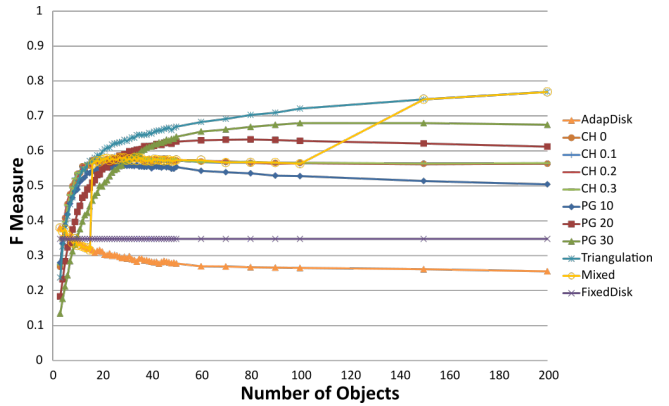


Figure 5: Accuracy for GoogleWiFi scenario.

Figure 5 shows the results for this dataset. We advocate for using a mixed algorithm when any information about the possible positions of the objects is completely unknown; however, it should be adapted for scenarios where more information is available (e.g., road networks), where the results of the different approaches might vary.

4 CONCLUSIONS AND FUTURE WORK

As moving object trajectories and map information could be unavailable, we aimed at providing location-based services with a better accuracy than assuming that the real coverage area of a wireless device is a disk of a fixed radius around such a device. In particular: 1) We have presented different approaches that estimate the coverage area of an object based only on the location of the detected objects, 2) Such algorithms have been evaluated in many different synthesized and real scenarios to compare their accuracy, including a combined algorithm that adapts itself (to the number of detected objects) and always behaves better than assuming a disk with a fixed radius.

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REFERENCES

- [1] S. D. Hermann, M. Emmelmann, O. Belaifa, and A. Wolisz. 2007. Investigation of IEEE 802.11k-based Access Point Coverage Area and Neighbor Discovery. In *32nd IEEE Conference on Local Computer Networks (LCN'07)*. 949–954.
- [2] J. Robinson, R. Swaminathan, and E. Knightly. 2008. Assessment of Urban-scale Wireless Networks with a Small Number of Measurements. In *14th ACM Intl. Conf. on Mobile Computing and Networking (MobiCom'08)*. 187–198.
- [3] R. Verdone, D. Dardari, G. Mazzini, and A. Conti. 2010. *Wireless Sensor and Actuator Networks*. Academic Press.