

August 2017

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Recommended Citation

Swapnil Gaikwad and David Anastasiu. "Optimal constrained wireless emergency network antenna placement" *2017 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computed, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCOM/IOP/SCI)* (2017). <https://doi.org/10.1109/UIC-ATC.2017.8397562>

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Optimal Constrained Wireless Emergency Network Antenna Placement

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Abstract—Communication is paramount, especially during a natural disaster or other emergency. Even when traditional lines of communication become unavailable, emergency response teams must be able to communicate with each other and the outside world. To facilitate this need, major cities across the United States are deploying wireless emergency networks (WENs) that serve as a secure communication channel between emergency response points (police stations, shelters, food banks, hospitals, etc.) and the outside world. An important question when designing such networks is identifying the locations within the city where access points (APs) should be placed to construct a reliable WEN. We propose a framework for identifying the optimal placement of wireless network antennas within a city, given multiple criteria constraints, and present our initial efforts to realize this framework.

Index Terms—microwave antenna, network planning, wireless emergency network, constrained optimization, line of sight.

I. INTRODUCTION

Communication is paramount in case of a natural disaster or other emergency. A large earthquake or flood may lead to loss of power or broken cables that can hinder traditional lines of communication (e.g., land-lines or cellular phones). Still, emergency response teams must be able to communicate with each other and the outside world. To facilitate this need, the City of San José Office of Emergency Services (OES) and other similar offices in major cities are deploying wireless emergency networks (WENs) that serve as a secure communication channel between emergency response points (police stations, shelters, food banks, hospitals, etc.) and the outside world. An important question when designing such networks is identifying the locations within the city where access points (APs) should be placed to construct a reliable WEN.

In this paper, we present a novel framework that will allow identifying the best placement of wireless access points within a city given several types of constraints. Finding the optimal placement of APs is a multi-constrained optimization problem. While these types of problems have been studied for many years, the unique constraints posed by the WEN AP placement domain make existing algorithms insufficient. A WEN is generally composed of multiple APs connected via microwave antennas capable of high speed data transmission. In addition to constraints posed by physical limitations of the antennas (e.g., signal transmission range, transmission type

– sector or point-to-point), the problem imposes several other hard and soft constraints. We consider the following types of constraints on the overall network:

- *Antenna type*. Wireless network antennas come in different types. Directional (point-to-point) antennas must be pointed directly at the receiving antenna to allow communication. Multidirectional (sector) or omnidirectional antennas have a much wider signal reception/transmission cone, at the cost of smaller coverage (shorter signal range).
- *Range*. Given the transmission signal strength and type of the i th antenna, its signal can reliably be transmitted up to d_i km.
- *Line of sight (LOS)*. Due to their increased coverage, directional antennas are often used in WENs. However, there must be clear line of sight between the transmitting and receiving antennas.
- *Node priority*. Node placement cannot be random in a WEN. APs must be placed at each identified emergency response point (hospitals, police stations, food banks, shelters, etc.), and city-owned properties should be given preference when choosing placement locations for other APs.
- *Minimum degree*. To ensure network reliability even in the event of the collapse of some APs (e.g., due to an earthquake), each AP should have LOS to a minimum of k other APs.
- *Mobile APs*. The system should allow for one or more mobile APs which can be used to enhance bandwidth or coverage when needed. This calls for a time and cost effective solution to the optimization problem, allowing near-real-time placement of mobile APs.

There has been little research done to solve this problem. Most academic works have focused on measuring the effects that distance and barriers have on the signal strength between two antennas, or on automatic adjustment of an antenna to capture the strongest signal from a transmitter. A few recent works [1]–[5] have addressed the related problem of antenna placement in millimeter-wave networks (mmWave). While these antennas have some of the same constraints (e.g., LOS, range), their range is much more limited (up to 200m). Szyszkowicz et al. [4] and Palizban et al. [5] both assumed

structures in the city to be at equal altitude, considering only the polygon shapes of buildings on a flat map as potential signal transmission obstacles. Moreover, none of the works consider the additional constraints imposed by a WEN.

There are several tools available online, most of them created by manufacturers of microwave antennas, that are designed to help users decide whether there is clear LOS between two points on a map. However, very few of them consider man-made obstacles when predicting LOS. While tools provided by Solvise [6] and HeyWhatsThat [7] consider buildings as potential obstacles, other tools [8], [9] only consider natural topologies (e.g., hills) when predicting LOS. Building heights in existing systems are generally queried using the Google Maps Elevation API [10]. Additional signal barriers, such as trees, are not considered by any of the existing tools. In contrast, we propose an extensible framework that automatically identifies the optimal network placement, respects additional constraints imposed by the WEN domain, and utilizes multiple sources of structure height data to ensure accurate LOS estimates between chosen AP locations.

The remainder of the paper is organized as follows. Section II introduces our proposed framework, giving an overview of its component parts. Section III presents two novel algorithms for estimating line of sight between two locations in a city. We describe our evaluation methodology in Section IV, analyze our experimental results in Section V, and Section VI concludes the paper.

II. PROPOSED FRAMEWORK

A. Wireless emergency network planning

In traditional wireless network planning, one is primarily concerned with signal coverage, as many clients should be able to use the network from the covered area. On the other hand, WEN planning is primarily concerned with broadband connectivity between a set of distant priority sites within a city. Coverage is then expanded via traditional techniques such as WiFi or WiMAX local networks. The long distance between priority sites often requires the use of point-to-point microwave antennas like the ones shown in Figure 1. Mobile communication towers, which can be mounted on top of vehicles, can also be used to provide increased transmission bandwidth or temporary coverage in an area. In addition to physical constraints of the antennas used in the transmission, the WEN placement problem has additional constraints, which were listed in Section I.

The proposed framework for solving the optimal constrained WEN antenna placement problem has two components. First, we will design a system that can provide efficient LOS estimates between different points on a map, while taking into consideration topography, structure heights, and vegetation that may interfere with LOS between points. Existing systems utilize Google Earth and Google Maps data for this task, which



Fig. 1. Tower with several microwave antennas.¹

is highly inaccurate for long distance LOS estimates, accounting only for some large buildings in cities and in general assuming a flat earth. Second, given efficient and reliable LOS estimates, we will devise a *min-k degree multi-constrained optimization* method that will provide an optimal configuration of the WEN given input constraints. The algorithm will take as input a list of all suitable locations for placing WEN antennas in the city and their associated priorities, a list of antennas that are part of the WEN and their physical characteristics, and the minimum number of k potential LOS links that each AP should have available.

The optimization algorithm we plan to use to solve this problem will be based on techniques borrowed from Recommender Systems. Assuming a set of already selected optimal points, the next AP point can be selected by first solving a top-N recommendation problem with side-information, retrieving a ranked list of the most “similar” APs, i.e., those with the highest connectivity and reliability score based on terrain and other constraints. From the top-N points, the chosen AP will be the first one that passes each of the imposed constraints. While the problem is not convex, matrix and tensor factorization based recommender systems models can capture some inherent structure in the problem that can lead to good solutions overall.

¹Image source: https://en.wikipedia.org/wiki/File:Frazier_Peak_tower_and_Honda_Element.jpg. Author:GeorgeLouis (talk). Date: September 2008.

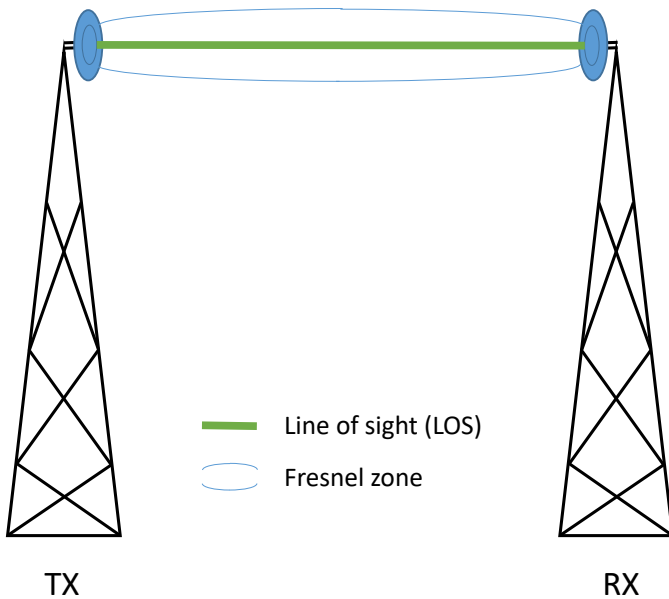


Fig. 2. Microwave communication between a transmitting (TX) antenna and a receiving (RX) antenna.

B. Microwave links

A critical component in WEN planning are microwave network links. Microwave links use high frequency beams of radio waves (in the microwave frequency range, thus the name) to transmit data between two fixed points. Figure 2 shows an example of two such points. The transmission point (TX) modulates the radio signal to encode data and sends it out into “free space,” the void directly in front of the antenna used to transmit the signal. As the radio waves propagate through the atmosphere, some of the signal is lost, yet on a clear day a microwave transmission can be received up to 65 km away. The receiving (RX) antenna collects the signal sent by the TX antenna and translates the modulation into binary data.

While microwave links can transmit large amounts of data over great distances at nearly the speed of light, they require a clear path between the TX and RX antennas (LOS) for a successful transmission. Buildings, trees, overpasses, and any other obstacles in the transmission path must be overcome by changing the position of one or both of the TX and RX points or using a bridge to relay information, as long as the bridge point has a clear path to both TX and RX points. A microwave signal that passes through a tree may be somewhat strong in the winter but can become significantly weaker once the tree grows new leaves in the spring.

Reflective surfaces along the transmission path, such as bodies of water or smooth terrain, will cause radio waves to reflect off those surfaces and either never arrive at the RX point or arrive out of phase, causing degradation in the transmission [11]. Fresnel zones, shown in Figure 2 and named after physicist Augustin-Jean Fresnel, who invented the theory, are concentric ellipsoidal volumes in the transmitted radiation pattern [12] that help visualize the reflection potential of the radio waves. Presence of barriers or objects within

more than 40% of the fresnel zone will severely degrade the transmission signal. When predicting LOS clearance, it is thus important to consider not only the direct line between the TX and RX antennas, but also the fresnel zone for the link.

C. Improving height estimates

We will utilize Big Data and computer vision technologies to expand an existing geographic information system (GIS) with the ability to predict and visualize LOS between two given points. A number of open-source Map visualization libraries exist (e.g., ViziCities [13], or Tangrams [14]) that can be adapted to account for topography data captured by US Geographic Survey and satellite data from the GMTED2010, SRTM, and NED satellites. While the primary function of the system will be to efficiently estimate LOS between two points on the map, it will also be able to accurately visualize in 3D the path between the points. The system will use additional point altimetry information gathered through Data Mining to improve LOS estimates. For example, city building permit data can be used to estimate building heights at certain addresses based on the number of and type of floors in the building. Moreover, geo-tagged photographs on social media sites like Twitter or Instagram can be used to extract building height estimates when objects with known heights (e.g., light posts) can also be detected in the picture.

III. ESTIMATING LINE OF SIGHT

A wireless network loses its efficiency due to obstructions in path of communication. Microwaves used in wireless communication reflect off of buildings. When we select two probable antenna locations, we should make sure there is clear line of sight for full utilization of the wireless channel. In this section, we will detail two algorithms that can be used to predict LOS between two arbitrary points in a city.

A. GIS Database

We chose the city of San José as the test location for our methods. We downloaded San José map data from Mapzen [15], which in turn uses OpenStreetMap (OSM) data [16]. We import this data in a PostgreSQL database, which we use as our chosen Geographic Information System (GIS). The OSM data is 2-dimensional, providing only latitude and longitude for buildings in the city. The third dimension, i.e., the height of each building, was obtained using LiDAR data [17]. This data contains records in the Lambert Conical projection format, which we had to convert to the WSG84 projection format of the OSM records. The guide provided by Yuriy Czoli [18] was very helpful in successfully converting between LiDAR and OSM data records. We used the libLAS library [19] and PostGIS tools [20] to do the actual conversion and stored the height of each building in an additional field associated with the building record. When more than one LiDAR altitude records was present for a building, we used the average of those records to derive the building height.

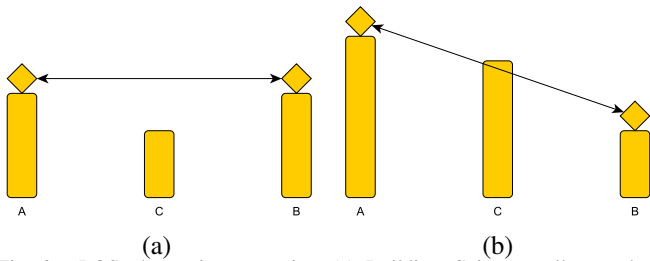


Fig. 3. LOS obstruction scenarios. (a) Building C is not tall enough to obstruct the LOS between buildings A and B. (b) Building C obstructs the LOS between buildings A and B.

B. Sequential LOS

Our straight forward baseline LOS estimation method works by querying the GIS for all buildings C between the two selected points (A and B), which are polygons intersecting the line segment between the points. Then, for each returned building, we verify whether its height is higher than the intersecting point on the slope from the A to the B points. Figure 3 shows two scenarios for one such building C. In the first case (a), it is clear that building C will not obstruct LOS between buildings A and B. The three buildings start at the same altitude, and buildings A and B are both taller than building C. In the second case (b), it is not as clear, as building B is not as tall as building C. Note, however, that LOS would be clear, for example, if building C and B were the same height. Specifically, the height of building C must be lower than the height of the transmission line (connecting the tops of the A and B buildings) at building C.

One potential problem with the SLOS method is the case when the transmission line passes narrowly between two tall structures. As noted in Section II-B, the path between the TX and RX antennas should be clear not only on the direct line between them, but also within at least 60% of the fresnel zone of the two antennas. Figure 4 shows one such potential example. To account for this scenario, we execute two additional queries, for parallel lines situated at γ m on each side of the transmission line. SLOS then checks the height of buildings that were not present in the original query result to ensure they will not create obstacles in the transmission path.

C. Tiled LOS

In the case of a clear line of site, the SLOS algorithm has to check each building that intersects the transmission line to ensure they will not obstruct transmission. We propose an efficient data structure that can significantly reduce the number of buildings whose height must be retrieved and considered, based on a hierarchical tiling of the city's surface area. Figure 5 shows an initial decomposition of the surface area into equally sized tiles. Note that the number of tiles may be different between levels. In the example, *green tiles* have a maximum height lower than the minimum intersecting point of the transmission line slope, while *red tiles* exceed that height.

Given the number of tiles per level, the tiling algorithm is straight-forward. For each tile, we pre-compute and store

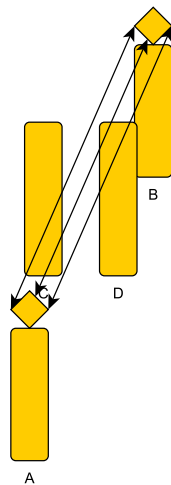


Fig. 4. Potential fresnel obstruction.

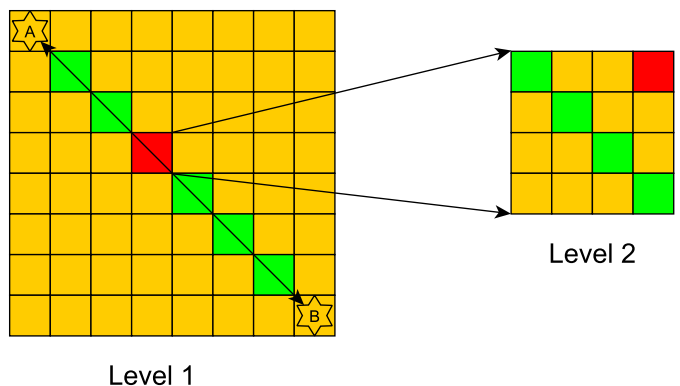


Fig. 5. Surface area tiling in the TLOS algorithm. *Green tiles* have a maximum height lower than the minimum intersecting point of the transmission line slope, while *red tiles* exceed that height.

the highest elevation of any building in the tile. Note that the maximum heights of lower-level tiles can be easily aggregated to find the maximum height of a higher level tile. The highest elevation in a higher level tile is the maximum elevation among all child tiles. When predicting LOS, we first check the maximum height of tiles intersecting the transmission path. If a tile's maximum height does not obstruct the transmission path, we can skip checking all the buildings within that tile. On the other hand, in the case of an obstruction, we can dig into the next lower level, retrieving child tiles that intersect the transmission path. At the lowest (leaf) level, data is stored without tiling and we determine the line of sight using the baseline SLOS approach. This method will significantly reduce number of calculations required to solve the LOS prediction problem. Note that this work is in progress and we have not yet finished implementing TLOS. We will thus not be including this method in our experiments.

IV. EXPERIMENT SETUP

In order to determine the effectiveness of our baseline method, we compared its ability to detect clear or obstructed

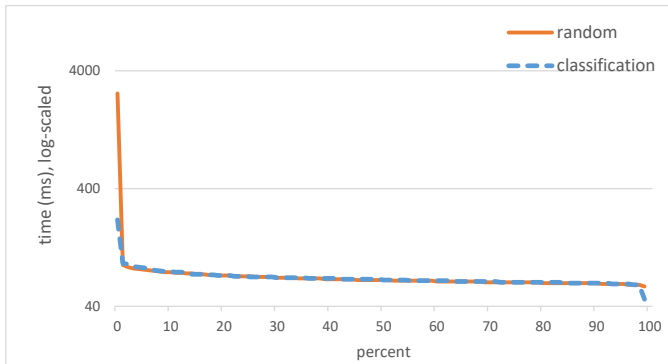


Fig. 6. Distribution of execution time among the 200 queries in our effectiveness experiment.

LOS, which is solved as a classification problem. We use *accuracy* to measure the effectiveness of our method, which is defined as the ratio between the number of correctly predicted samples and the total number of samples predicted. Additionally, we report *precision*, *recall*, and *F1-measure* for the prediction. Precision is defined as the fraction of samples that are relevant in the prediction, recall is the fraction of relevant samples that were successfully predicted, and F1-measure is the harmonic mean of the precision and recall scores. Note that precision, recall, and F1-measure depend on which class is considered relevant and produce different results in an imbalanced binary classification scenario. We measure efficiency as the time (wall-clock) taken by each query, in milliseconds.

A. Execution environment

Our baseline method, SLOS, was executed, without other running programs, on a server with dual-socket 12-core 2.5 GHz Intel Xeon E52680 v3 (Haswell) processors and 384 Gb RAM. We used PostgreSQL version 9.6.1 to host our GIS database. As a proof of concept, we used a subset of OSM and LiDAR data covering the city of San José, which takes up 685GB of storage, including all indexes. While our system has 24 cores available, the PostgreSQL engine used only one core for executing each query. In all experiments, we set $\gamma = 6$.

V. RESULTS & DISCUSSION

We executed two experiments in order to test the efficiency and effectiveness of our baseline SLOS method. In the first experiment, we compared the ability of SLOS to detect clear or obstructed LOS on 200 random queries. We selected LOS queries by choosing two random buildings from the city of San José and predicting the link between them. We then obtained the link’s real LOS status using an external LOS validation tool [7]. Among the 200 links, only 7 were misclassified, resulting in an accuracy of 96.5%. While this result is encouraging overall, it turns out that our random point sampling strategy resulted in a majority of obstructed links (197). With regards to obstructed links, the method performed quite well, resulting in 0.9948 precision, 0.9745 recall, and

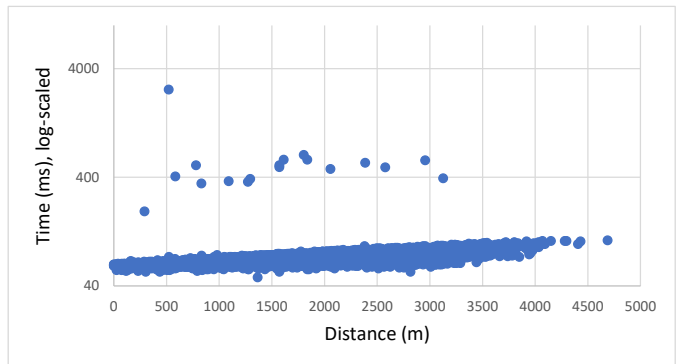


Fig. 7. Efficiency of line-of-sight queries using the SLOS algorithm.

0.9845 F1-measure. The method did not perform well with regards to clear LOS links, resulting in 0.0052 precision, 0.3333 recall, and 0.0103 F1-measure. Additional experiments are needed to validate the effectiveness of the method for clear links as well as obstructed links.

On average, the distance between selected points in the queries was 1266 m. The *classification* line in Figure 6 shows the distribution of execution time among the 200 queries in our effectiveness experiment. Note that the y-axis is log-scaled. Most queries took between 60 and 100 ms to execute. As a way to further investigate the efficiency of our method, we executed a set of 20,000 random LOS queries, recording the execution time for each. The *random* line in Figure 6 shows the distribution of execution times among these queries, which almost exactly matches that of the classification experiment, with the exception of the extreme start of the distribution. A few points in our classification experiments took 150-217 ms to execute. Similarly, a few of the points in our random query experiment took 500-2567 ms to execute. However, we could not see a clear correlation of between-point distance and query execution time among these few points in either experiment. We conclude that the high execution times in these few queries are likely due to the GIS system loading certain indexes from disk.

To better understand the relationship between query execution time and distance in our experiments, we computed the correlation of the two variables. The 200 sample classification experiment results showed a correlation of 0.49, while the 20,000 sample random experiment results showed a correlation of 0.21. Figure 7 shows a scatter plot of the random experiment results, denoting the distance and execution time of each query. While many queries take between 50–150 ms, the graph shows a clear slightly positive correlation between distance and execution time. Queries for points farther than 4,000 m apart take longer to execute, in general, than those closer together.

While 50–100 ms may seem pretty fast to compute the LOS prediction for a pair or points, solving the optimization problem requires hundreds of thousands of such computations, making SLOS unsuitable for the task. The TLOS algorithm and other methods that can prune the search space and

avoid retrieving and considering all the data for buildings on the transmission path are key to efficient near-real-time solutions to the WEN planning problem. In the continuation of this work, we will investigate such methods and propose efficient solutions to both the LOS estimation and the wireless emergency network planning problems.

VI. CONCLUSION

In this paper, we first presented a general framework for solving the optimal constrained wireless network antenna placement problem, and then detailed two algorithms for efficiently identifying whether there is a clear line of sight between two locations in the city, which is a critical component in the framework. Our first baseline algorithm, S_{LOS} , uses off-the-shelf GIS aware database systems and open-source data to effectively solve the problem, resulting in 96.5% accuracy in our initial experiments. While its average execution time may impede it from solving the optimization problem in a reasonable amount of time, our Tiling Line of Sight (T_{LOS}) method promises much higher efficiency by drastically reducing the number of structures whose height must be checked to ensure it does not obstruct LOS.

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