Semantic Mobile Base Station Placement

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Abstract. Location of Base Stations (BS) in mobile networks plays an important role in coverage and received signal strength. As Internet of Things (IoT), autonomous vehicles and smart cities evolve, wireless network coverage will have an important role in ensuring seamless connectivity. Due to use of higher carrier frequencies, blockages cause communication to primarily be Line of Sight (LoS), increasing the importance of base station placement. In this paper, we propose a novel placement pipeline in which we perform semantic segmentation of aerial drone imagery using DeepLabv3+ and create its 2.5D model with the help of Digital Surface Model (DSM). This is used along with Vienna simulator for finding the best location for deploying base stations by formulating the problem as a multi-objective function and solving it using Non-Dominated Sorting Genetic Algorithm II (NSGA-II). The case with and without prior deployed base station is considered. We evaluate the base station deployment based on Signal to Interference Noise Ratio (SINR) coverage probability and user down-link throughput. This is followed by comparison with other base station placement methods and the benefits offered by our approach. Our work is novel as it considers scenarios where there is high ground elevation and building density variation, and shows that irregular BS placement improves coverage.

Keywords: Base Station Placement · Semantic Segmentation · Drone Imagery.

1 Introduction

Mobile communication technologies have become the predominant mode of connectivity for present day devices such as mobiles, tablets, wireless sensor nodes, and Internet of Things (IoT) devices. This has triggered widespread deployment of mobile base stations all over the world. With every generation of wireless technology, the density of base stations per unit area has been increasing due to an increase in carrier frequency. As a result, the deployment strategy has transitioned from hexagonal cells to random deployment in Voronoi like cells based on user density [1]. Since the signal received by a user is a function of base station location, strategic placement based on ground surface elevation, location of blockages such as buildings, vegetation etc. improves coverage, especially at higher carrier frequencies such as at millimeter waves.

Recently, drones have entered the commercial consumer market, reducing the cost of acquiring aerial imagery. In addition to RGB images, aerial infrared,
depth data and multi-spectral images are also available from them. Due to higher resolution in these images compared to satellite images along with recent advances in deep learning, many new applications have emerged such as in solar panel deployment [2]. The use of these learning techniques has resulted in a drastic reduction in cost and time spent on manual surveying.

2 Related Work

Many research groups have historically explored BS placement for optimizing wireless communication [3]. Butterworth et. al. [4] have shown how various placement strategies affect communication performance for in-building scenarios. For outdoors, placement approaches based on evolutionary algorithms have been used in [5,6] to improve network performance. In [7], a k-means based approach has been used to find the optimal location based on user density. In these works, the effect of ground surface elevation was not considered. Recently, the use of aerial BS on drones for handling network load during hotspot scenarios has been used for ensuring robustness of wireless connectivity [8], though this approach might not be suitable during rain, high speed winds etc.

However, telecom operators primarily use commercial RF planning tools like WinProp [9] for network deployment since the sites are constrained by presence of buildings, objects etc. RF engineers select candidate locations and check various BS configurations for best coverage and deployment cost trade-off. This can be done using tools such as the Huawei 5G Wireless Network Planning Solution which uses ray tracing channel model on GPU, or the Vienna System Level Simulator [10] which uses statistical model for simulation of coverage on CPU.

3 Our Approach

Our approach involves two phases. In the first part, to account for the location of objects, we perform semantic segmentation of the aerial image of the location where we want to deploy BSs. Then, the segmentation map along with the elevation data (DSM) is used to create a 2.5D model of the scenario. Candidate base stations, user and building locations are also generated based on the segmentation map. Then, in the second phase, NSGA-II [11] is used to select the best BS location based on the SINR of users calculated using Vienna System Level Simulator. Each of these steps have been described in the following subsections.

3.1 Semantic Segmentation

We use DeepLab v3+ [12] for semantic segmentation. For training the network, we used the ISPRS Potsdam dataset [13]. All the labels (imperious surfaces, buildings, low vegetation, tree, car and clutter) with class weights 0.2673, 0.2299, 0.2567, 0.1761, 0.01648, and 0.05354, respectively were used for training to account for class imbalance. Each of the tiles in the RGB images and labels of the
training set were randomly cropped to 800 × 800 patches and then randomly zoomed in and out, flipped and rotated for data augmentation. We used Xception [14] pre-trained base network, fine tuned using ADAM for 20 epochs with learning rate $10^{-4}$, mini-batch size 4 and 230 iterations per epoch on a NVIDIA GeForce RTX 2070. We also used $L_2$ regularization of 0.005 and shuffled the training data in every epoch. For validation, 25% of the training data was used. For prediction, a sliding window of size 800 × 800 with an overlap of 400 pixels was used to predict the labels and the results were stitched together.

Each of the segments corresponding to buildings were used with elevation data from the DSM to create blockages. Users were placed at an elevation of 2m above the elevation of segments corresponding to impervious surfaces, low vegetation and clutter. Candidate BS locations were created on a regular grid spanning the entire area, except where trees, clutter or car segments were present. This was done since the clutter class contained water bodies and other objects which could not be considered as candidate locations.

### 3.2 NSGA-II based placement

We now formally introduce the multi-objective function used for NSGA-II in our approach. Let each $SINR_i$ denote the signal strength of the $i^{th}$ user, $N$ be the total number of users, $M$ be the number of BS deployed, $M_{max}$ be the maximum number of BS we wish to deploy in a given area, and $SINR_{threshold}$ be the threshold above which we want to maximize the signal strength. The following three objective functions are optimized in our approach:

- Maximize the total signal strength of users near buildings and roads:
  \[
  \min \left( - \sum_{k}^{} SINR_k \right) \tag{1}
  \]
  Here, $k$ denotes the users near buildings and roads.

- Minimize the number of BS deployed:
  \[
  \min M, \text{ subject to } 1 \leq M \leq M_{max} \tag{2}
  \]

- Maximize the number of users with SINR greater than a threshold:
  \[
  \min \left( - \sum_{i=1}^{N} \mathbb{I}(SINR_i > SINR_{threshold}) \right) \tag{3}
  \]
  Here, $\mathbb{I}$ denotes the indicator function.

We used Vienna simulator [10] for calculating the value of the objective functions for chromosomes of the population. To simulate Long Term Evolution (LTE) scenario, we used a carrier frequency of 2 GHz with three sector BS composed of 3 antennas having a Half Power Beam Width (HPBW) of 65 degrees [15]. The simulator was also modified to support arbitrary shaped blockages. The
function to check LoS was modified using the MATLAB geometry toolbox for 2D/3D geometric computing \cite{16}. Each base station location is binary encoded and an array of binary encoded locations is used to represent a particular BS configuration or a chromosome in NSGA-II.

4 Results and Analysis

4.1 Semantic Segmentation

We report the class-wise recall, Intersection over Union (IoU), and Boundary F1 (BF) contour matching score on the test set in Table 1. For the sub-6 GHz carrier frequency case, only a limited set of objects act as blockages. Thus, for the case of LTE, since a carrier frequency of 2 GHz is used in Vienna Simulator, we are mainly concerned with the performance of the model on a subset of classes, namely, impervious surfaces, buildings, and tree.

| Class              | Recall  | IoU     | BF Score |
|--------------------|---------|---------|----------|
| Impervious Surfaces| 0.80821 | 0.76650 | 0.92831  |
| Building           | 0.93768 | 0.87353 | 0.89388  |
| Low Vegetation     | 0.74346 | 0.57438 | 0.80486  |
| Tree               | 0.81295 | 0.61912 | 0.89304  |
| Car                | 0.98158 | 0.58406 | 0.94777  |
| Clutter            | 0.59747 | 0.29685 | 0.53180  |

Table 1: Class wise metrics of Semantic Segmentation.

4.2 Placement without Prior Deployed BS

![Simulation Setup](image)

Fig. 1: Top view of Scenario I with candidate BS location

First, we considered the case when no existing base stations were present. The maximum number of base stations to be deployed, $M_{\text{max}}$, was set to 6. In
the first scenario, we considered the tiles labeled as 5_11, 5_12, 5_13, 6_11, 6_12, 6_13, 7_11, 7_12, 7_13 in the Potsdam dataset. The top view of the 2.5D model with candidate BS locations (red), and users (yellow: users near buildings and on roads, green: other users) generated have been shown in Fig. 1.

Fig. 2: Scenario I Solutions generated by NSGA-II optimizer

The results of NSGA-II optimizer have been shown in Fig. 2. The plot in (c) shows the solutions generated by the optimizer with the color varying with every iteration. The axes represent the objective functions used in our formulation in sub-section (3.2). It can be seen that it generates a better solution with every iteration. The 2D versions of this plot have been shown on the left for comparison. The total SINR, i.e., sum of SINR of the users near buildings and on roads increases with the number of base stations deployed as seen in (a). Similarly in (b), the number of users with $SINR > 10$ dB also follows the same trend.

In Fig. 3, optimal solutions for number of base stations = 3, 4, 5 and 6 from the final population based on non-dominated sorting were chosen and plotted. We then performed link level simulations for each configuration and plotted the SINR coverage probability and user downlink throughput CDF using Vienna System level Simulator in Figs. 4 (a) and (b) respectively. In (a), we observe that the SINR coverage probability increases as number of BS increases from 3 to 5. For 6 BS, however, the probability of coverage above 0 dB is almost identical to the case of 5 BS because interference from non-serving base stations starts dominating. Therefore, we infer that deploying 6 BS offers almost identical coverage as deploying 5 BS. Further, in (b), we see that the user downlink throughput CDF decreases with increasing number of BS. This implies that deploying more BS decreases the probability of a user having a lower throughput. We again observe a high degree of overlap for 5 and 6 BS cases. Therefore, for the given scenario, we conclude that deploying 5 or 6 BS would result in similar coverage, however, 6 BS will have a higher throughput for users.
4.3 Placement with Prior Deployed BS

We also consider the case when new base stations are to be deployed given the location of existing base stations. Here, NSGA-II only finds optimal locations for the new base stations. We assumed that 3 base stations (represented by black) were already present as shown in Fig. 5.

After using NSGA-II, the optimal solution for total number of base stations \(= 3, 4, \) and 5 from the final population based on non-dominated sorting were chosen and plotted in Fig. 5. The SINR coverage probability and user downlink throughput CDF have been shown in Figs. (a) and (b) respectively. The SINR coverage probability improves by deploying new base stations as shown in Fig. (a). In Fig. (b), we see that for 3 BS, the probability of a user having no throughput \((P(\text{throughput} < 0 \text{Mbps}))\) is 0.5. This is supported by the plot in Fig. (a), where we can see that about half of the users have no coverage (very low SINR). For 4 BS and 5 BS, \(P(\text{throughput} < 0 \text{Mbps})\) decreased to almost 0. However, the trend of a lower throughput CDF for more number of BS is not seen uniformly in this example. Unlike in section (4.2), this is potentially because of the presence of existing BS which are not at their optimal positions. Therefore for Scenario II, placing all BS using NSGA-II resulted in improved SINR coverage probability and user downlink throughput. However, when 3 BS were already present and remaining BS are placed using NSGA-II, only SINR coverage probability improved.
4.4 Effect of Using Blockages for Optimization

To quantify the effect of considering blockages (such as buildings) for calculation of SINR during optimization, we consider Scenario I in sub-section 4.2. However, this time we perform the optimization, once with blockages and without considering any blockages. As in the previous cases, the ground surface elevation was used for simulating the scenario in both the cases. After obtaining the optimal base station locations, we plotted the SINR coverage probability for 3 and 5 base stations in Fig. 7a. It can be seen that by considering blockages for finding optimal base station location, the SINR coverage probability improved as compared to not considering them during optimization. The corresponding base station locations (for the dashed red and black lines) have been shown in Fig. 7b. It is important to note that building density is high for the scenario under consideration. As blockages were not considered, the optimal base station locations form a convex polygon unlike in Figs. 3(b) and (d).

4.5 Comparison with Other Methods

We compare our NSGA-II based placement approach to the iterative k-means approach proposed by Toros et al. in [7]. The SINR coverage probability for
Fig. 6: Effect of deploying new BS.

optimal placement of 3, 4 and 5 base stations from NSGA-II based optimization and iterative k-means has been shown in Fig. 8a. We have considered the same Scenario I as in subsection 4.2 for this comparison.

Fig. 7: Effect of considering blockages in optimal BS placement.

(a) Improvement in SINR coverage probability
(b) Optimal BS location when blockages are not considered during optimization.

Iterative k-means approach: From Fig. 8a we can see that despite increasing the number of base stations, the SINR coverage probability did not improve significantly for placement using the iterative k-means approach. This can be attributed to the lack of using SINR while computing the optimal base station location. The method uses SINR only for finding the Most Unserved Sector (MUS). We also observe that for the scenario under consideration, 3 base stations placed using NSGA-II provide better SINR coverage probability than 5 base stations placed using k-means approach.

Standard Genetic Algorithm: We maximized the number of users with $SINR > 10dB$ as mentioned in 3 since standard GA is single objective. The rest of
the parameters were kept the same. For finding the optimal location of deploying 3, 4 and 5 base stations, we separately ran the GA optimizer thrice by varying $M_{max}$ each time as shown in Fig. 8b. It can be seen that placement using NSGA-II gives slightly higher SINR coverage probability compared to GA for 5 and 4 base stations. This improvement is not seen for 3 base stations. Therefore, the benefit of multi-objective optimization is considerable only when optimal number of base stations are deployed. Another observation is that single objective optimization with standard GA gives higher SINR coverage probability as compared to the iterative k-means approach shown in Fig. 8a.

5 Conclusion

In this paper, we proposed a pipeline for optimally placing mobile BS by considering semantic information extracted from aerial drone imagery using deep learning. We show how our placement approach affects average user down-link throughput and SINR coverage probability. The key contribution of this paper included quantifying effect of considering blockages for optimal base station placement for an LTE network when building density and surface elevation variation are high. Future work will involve finding optimal BS location for heterogeneous networks comprising of multiple mobile communication technologies.

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