RSU Placement Optimization in Vehicular Participatory Sensing Networks

Teerawat Kumrai*†, Kaoru Ota*, Mianxiong Dong‡, and Paskorn Champrasert†
*Muroran Institute of Technology, Japan
†Chiang Mai University, Thailand
‡National Institute of Information and Communications Technology, Japan
Email: teerawat.kumrai@gmail.com, ota@csse.muroran-it.ac.jp, mx.dong@nict.go.jp, paskorn@eng.cmu.ac.th

***Abstract*—This paper proposes a multi-objective optimization evolutionary algorithm for placement of roadside units (RSUs) in participatory sensing using vehicular networks. The proposed algorithm heuristically optimizes RSUs' communication coverage area in a city with the minimal number of RSUs. The extensive simulation results show the efficacy of the proposed algorithm comparing to a traditional placement algorithm.**

I. Introduction

With the wide proliferation of mobile devices (e.g., smart phones, tablets) as well as the ubiquitous availability of network services, participatory sensing has gained lots of attentions in recent years [1]. It enables to broadly collect information from the mobile devices with embedded several kinds of sensors. Vehicles equipped with sensors and wireless communication devices are rich information resources because of the high capacity and highly distributed and dynamic nature. Information collected from the vehicles are useful for various purposes: traffic control, safety assist, environmental monitoring, SNS, etc. The vehicles send the information to the Internet through either cellular networks (e.g., 3G, LTE) or RSUs (e.g., public wifi access points) [2]. The cellular networks are pervasive such that the vehicles can access to the Internet at almost anywhere and anytime; however, its cost remains high. Usually in the participatory sensing, users are voluntary and it is important to give them incentives to collect information. Thus, using the RSUs are more attractive for the users in terms of the cost of the Internet access.

Communication coverage of RSUs, however, is biased in a city and the vehicles can access to the Internet only within a communication range of at least one RSU. If the RSUs are pervasively deployed in the city, the coverage will be extended but the RSU setup cost is too expensive (e.g., $13,000-$15,000 per RSU) which may impose access fee on the users of RSUs. Thus, the position of each RSU must be well-planned before deploying the RSUs. However, maximizing the communication coverage and minimizing the number of RSU are the conflicting objectives. Therefore, this problem is classified as a multi-objective optimization problem while the RSU placement problem has also been proved as an NP-complete problem [3]. To solve the problem, we propose the evolutionary algorithm (*EA*) which heuristically seeks the Pareto-optimal RSU position for RSU deployment process.

II. The Evolutionary Algorithm

A. Evolutionary Optimization Process

We first presents a big picture of the proposed multi-objective optimization EA. The EA performs its evolutionary optimization process to obtain a set of solutions called individuals. After the EA finishes, the set of individuals and their two objective values are provided to the decision makers. The decision maker will select one of the individuals for the RSU placement.

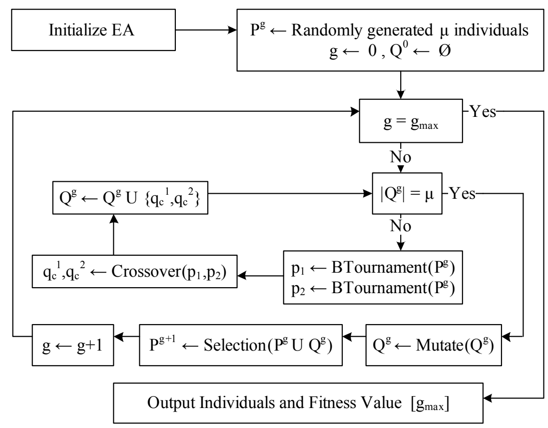

Fig. 1: Evolutionary optimization process

Figure 1 shows the algorithmic structure of the evolutionary optimization process. The initial population (P^0) consists of μ individuals that contain randomly-generated RSU positions. In each generation (g), a pair of individuals, called parents (p_1 and p_2), are chosen from the current population P^g using a binary tournament operator (`BTounament()`). A binary tournament randomly takes two individuals from P^g, compares them based on their fitness values, and chooses a superior one (i.e., the one whose fitness is higher) as a parent. Two parents reproduce two offspring (q_c^1 and q_c^2) with a crossover operator (`crossover()`). Each offspring is mutated with a mutation operator (`mutation()`). The binary tournament, crossover and mutation operators are performed repeatedly until the number of offspring ($|Q^g|$) reaches the population size (μ). Once μ offspring are reproduced, they are combined with the parent population P^g. Then, a selection operator (`selection()`) selects the top μ individuals from 2μ individuals in $P^g \cup Q^g$ as the next generation's population (P^{g+1}). This selection is driven based on fitness values of individuals. EA terminates its evolutionary optimization process when the number of the generations (g) reaches its maximum limit (g_{max}).

B. Individuals

In this paper, each individual consists of multiple segments, each of which represents an RSU, i.e., the number of segments in each individual is equal to the total number of RSUs in the city. The segment consists of three properties which are the status, x coordinate, and y coordinate. The status represents either two conditions where the RSU will be deployed at the coordinate (x, y) or not.

C. Optimization Objectives

This paper considers the communication coverage and the setup cost as two objectives in RSU placement optimization.
Coverage (F_{cov}): The communication area covered by all RSUs in the city. The city is divided to $X \times Y$ grids.

Let S is a set of N RSUs,

$$\forall s_i \in S, s_i = \{t_i, x_i, y_i\} \tag{1}$$

where t_i is the status of RSU i , and x_i and y_i are the coordinate x and y of the RSU. The communication coverage in the city is calculated as follows:

$$F_{cov} = \frac{[\sum_{x'=0}^{X} \sum_{y'=0}^{Y} g(x', y')]}{Total\ Road} \tag{2}$$

$$g(x', y') = \begin{cases} 1 & , if\ \exists j \in \{1, ..., N\},\ d_{(x_j, y_j),(x', y')} \leq R_j \\ 0 & , otherwise \end{cases} \tag{3}$$

where $d_{(x_j, y_j),(x', y')}$ is the Euclidean distance between the gird (x', y') to the roadside unit j. R_j is the communication range of RSU j. In Equation 3, when a grid which is the road in the city is covered by at least one RSU, the grid is considered as a covered communication area. The total communication area is the summation of the areas of covered grids.

Thus, the uncoverage area is calculated as Equation 4. The uncoverage area is considered as an objective, which requires to be minimized.

$$F_{uncov} = Total\ Road - F_{cov} \tag{4}$$

For the second objective, we use the number of RSU because the setup cost is highly dependent on the number of RSUs which requires to be minimized.
The Number of RSU (F_{num}): The total number of RSUs deployed in the city, i.e., $F_{num} = n$ where n is the number of segments in a finally selected individual.

III. Simulation Evaluation

A. Simulation Configurations

We use a simulated city to evaluate the proposed EA. We assume that at most 200 RSUs can be deployed in the city. An RSU's communication range is set as 250m. The city size is $5km \times 5km$, with a total road length of $50km$ divided 50×50 grids. Figure 2 shows the simulated city and the gray area depicts a road in the city. Other simulation parameters are set as: 100 populations, 15,000 max generations, $1/n$ mutation rate, and 0.9 crossover rate. We compare the performance of our EA with the uniform deployment (*UD*) of RSU.

B. Simulation Results

Figures 3 shows results of optimal solutions gained by the EA and UD, respectively. As shown in the figure, the EA successfully extends the communication coverage with less number of RSUs in the most of cases than the UD.

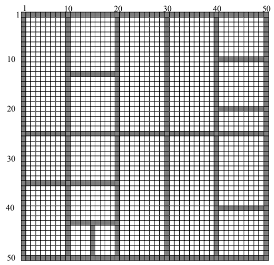

Fig. 2: Simulated city

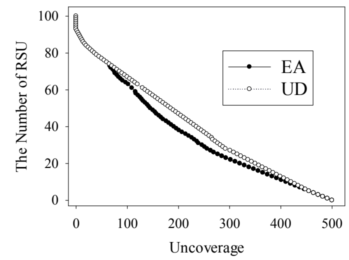

Fig. 3: Performance comparison between EA and UD

To show reproducibility of experiments, we further conduct 10 independent runs and compare the performance of the EA and UD based on results from all the runs. We use C-metric [4] to represent how the individuals of an algorithm outperform the individuals of the other algorithm, calculated below:

$$C(A, B) = |\{b \in B \mid \exists a \in A : a \succ b\}|/|B| \tag{5}$$

where $C(A, B)$ represents C-metric of algorithm A to B and $a \succ b$ represents individual a constraint-dominates individual b. $C(A, B)$ is calculated as the fraction of B's individuals that at least one individual of A constraint-dominates. Thus, if $C(A, B) = 1$, all of B's individuals are constraint-dominated by at least one of A's individuals.

We calculate the average of C-metric over all the run and results are summarized as follows: C(EA,UD) = 0.62 and C(UD,EA) = 0.01. The results conclude that the EA contributes to optimize the communication coverage and the number of RSU more effectively than the UD.

IV. Conclusion

This paper proposed EA to find appropriate sets of RSU positions to optimize the communication coverage and the number of RSUs. Simulation results show that the EA outperforms the UD of RSUs. As future work, we will conduct simulation experiments under more realistic scenarios.

Acknowledgement

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