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Probabilistic deployment of dissemination points in urban areas to support vehicular communication

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Abstract. This work presents a probabilistic constructive heuristic to support the design of roadside infrastructure for information dissemination in vehicular networks. We formulate this as a Probabilistic Maximum Coverage Problem (PMCP) and we intend to maximize the number of vehicles that get in contact with the infrastructure. We compare our approach with non-probabilistic MCP in simulated urban areas following a Manhattan-style topology with variable traffic conditions. The main contributions of this work are (i) the formal definition of the Probabilistic Maximum Coverage Problem, (ii) the application of PMCP to solve one instance of the problem of facilities allocation and (iii) the application of a probabilistic approach to model the volume of vehicles along the urban area, where the position of each vehicle is no longer considered deterministic, but it is treated as a probability function distributed over all the intersections. The vehicles no longer have a position. Instead, vehicles have a probability of being in a given position at a given instant of time. The results reveal that PMCP requires less dissemination points (DPs) to achieve similar coverage ratio than non-probabilistic MCP, while preserving the same samples deviation.

Keywords: vehicular networks, maximum coverage problem, information dissemination.

Introduction

Vehicular ad-hoc Networks (Hartenstein and Laberteaux, 2008) have attracted the attention of the research community due to its potential for improving urban mobility. Many works in the literature address several issues related to monitoring roads conditions (Eriksson *et al.*, 2008), vehicles performance (Johnson and Trivedi, 2011), driver's behaviour (Araujo *et al.*, 2012), traffic lights state (Koukoumidis *et al.*, 2011; Le *et al.*, 2011; Cai *et al.*, 2010), traffic monitoring (Waze, 2008; Rybick *et al.*, 2007), collaborative driving (Smaldone *et al.*, 2008), accident detection (Zaldivar *et al.*, 2011) and event detection (Thompson *et al.*, 2010) offering a large spectrum of traffic information solutions.

Vehicles can communicate directly to each other, but the deployment of a minimum communication infrastructure along the urban area increases up to 5 times the message delivery ratio and reduces up to 35% the expected delivery time (Wu *et al.*, 2012). Such relevant gains are explained by the intrinsic nature of the vehicular networks, composed of dynamic nodes moving at high speeds, constantly changing the network topology. When considering rural areas and roadways, the gains are even stronger since the nodes are very disperse, making the vehicle-to-vehicle communication inefficient. In additional, the roadside infrastructure can be used to connect the vehicles to external systems in the Internet allowing the dissemination of information to/from drivers. The design of dissemination points presents several important issues, and this work focuses on a specific one:

> *Where do dissemination points have to be placed in a Manhattan-style topology to ensure the maximum coverage?*

This work formulates the Probabilistic Maximum Coverage Problem (PMCP) and applies this technique to compute where the dissemination points must be deployed. PMCP considers the flow of vehicles into the urban area to select the intersections that maximize the coverage ratio of vehicles. In this formulation, each intersection represents a set, each vehicle represents an element, and each element has a probability p of belonging to a set. The goal is to find the sets that maximize the expected cardinality of the union of the selected sets, i.e., amount of covered vehicles.

We investigate the benefits of incorporating a probabilistic model by comparing PMCP with MCP. A greedy heuristic to address the location of the dissemination points using the Maximum Coverage Problem (MCP) is presented in Trullols *et al.* (2009) and discussed in the third section (Greedy MCP). The simulations show that PMCP is able to achieve the coverage of almost 100% of the vehicles in a simulated urban area in Manhattan-style topology by deploying dissemination points in less than 7% of intersections, while MCP requires the deployment of dissemination points in 8.6% of the intersections to achieve similar coverage.

The main contributions of this work are:

(i) The formal definition of the Probabilistic Maximum Coverage Problem;

(ii) The proposal of a probabilistic approach to model the density of vehicles along the urban area;

(iii) The application of PMCP to solve one instance of the problem of facilities allocation.

The remainder of this work is organized as follows. The next section presents related works. The following section details the greedy heuristic for the MCP (Maximum Coverage Problem). The fourth section presents PMCP. Then, the fifth section discusses how the projection of the flow of vehicles is computed. The sixth section presents experiments and results. The last section concludes the document.

Related work

There are several proposals to model and solve, in specific scenarios, the problem of locating dissemination points to support the operation of vehicular networks. Some efforts follow a two-step approach based on the cellular telephony model. The first step splits up the region in geometric cells to reduce the complexity of the problem. The second one analyzes each cell individually in order to define the exact location of each dissemination point (DP) inside the cells. The work (Habib and Safar, 2007) adopts this strategy. After splitting the region, they apply an evolutionary approach to define the location of each dissemination point. The drawback of this approach is that the results are very dependent of the division made in the first step. PMCP differs from this method since it does not perform any split of the region under study.

Other efforts apply clustering techniques to solve the location of the dissemination points. Basically, they group the vehicles using some snapshot of the traffic. As an example of this strategy, Kchiche and Kamoun (2009) propose a greedy algorithm based on the centrality of group to select the best locations for dissemination points. The algorithm aims to maximize the performance of the message distribution system by reducing the global delay and the communication overhead of the messages. PMCP differs from this kind of approach since it uses a mobility model.

There are also some efforts that apply genetic programming to solve the problem of allocating dissemination points in a vehicular network. In a general sense, this kind of technique starts with an initial set of possible solutions that are combined through generations until some stop condition is reached. Cavalcante *et al.* (2012) apply this technique. The authors model the problem as a Maximum Coverage Problem and impose a limit of time. PMCP differs from this approach since it considers a probabilistic model to estimate the vehicles positions.

Finally, Trullols *et al.* (2009) present a greedy strategy to select the locations of the dissemination points. Throughout this text we will use the term Greedy MCP to refer to this heuristic. Greedy MCP is detailed in the next section.

Greedy MCP

Trullols *et al.* (2009) present a greedy heuristic for the Maximum Coverage Problem to locate the dissemination points. The authors assume three important conditions: (i) dissemination points are placed at intersections; (ii) each dissemination point has a range able to cover all the vehicles located at the intersection; (iii) the heuristic knows how many vehicles are at each intersection. Greedy MCP receives the inputs:

M: Matrix of intersections of size $r \times r$, where r represents the quantity of roads in the region under study. Each $M_{i,j}$ holds the amount of vehicles in the intersection of roads i and j.

α: Maximum quantity of dissemination points that can be deployed.

Algorithm 1 Greedy MCP.

```
Input: M, α;
Output: Selected intersections to receive DP;
 1: Sol ← ∅; {solution set starts empty}
 2: Quant ← 0; {no intersection selected yet}
 3: Cover ← 0; {no coverage}
 4: C_{i,j} ← UncoveredVehicles(M_{i,j}), ∀i, j; {coverage of each intersection}
 5: while Quant < α and Exists Uncovered Vehicles do
 6:     Select Max C_{i,j}; {intersection with more vehicles}
 7:     Sol ← Sol ∪M_{i,j}; {add intersec to solution}
 8:     Cover ← Cover + C_{i,j}; {update coverage}
 9:     Quant ← Quant + 1; {increase quantity of intersections}
10:     Remove Max C_{i,j} and Max M_{i,j}; {remove selected intersection}
11: end while
12: return Sol, Cover;
```

Algorithm 1.

Algorithm 1 shows an adapted version of the Greedy MCP. The original Greedy MCP heuristic requires full knowledge of the position of each vehicle along the urban area. In this work we have relaxed this assumption as it seems unpractical to be achieved in a real scenario, besides raising some important privacy issues. So, we rewrote Trullols heuristic to make a fair comparison with PMCP.

Lines 1-3 initialize the variables. The set *Sol* starts empty. The variable *Quant* holds the quantity of dissemination points deployed (starting as zero). The variable *Cover* holds the achieved coverage (also starting as zero). In line 4 the heuristic finds the coverage $C_{i,j}$ at each intersection, i.e., the amount of vehicles still not covered.

From lines 5 to 11 the heuristic loops selecting, at each step, the set (intersection) that offers the maximum coverage (line 6). The selected intersection is added to the set *Sol* (line 7). The variable *Cover* is increased with the coverage of vehicles achieved in $C_{i,j}$ (line 8). The *Quant* of dissemination points is incremented (line 9) and the selected intersection is removed from the data (line 10). The heuristic loops until it reaches the limit of α dissemination points deployed or it has covered all vehicles (line 5). Greedy MCP is used as a baseline for PMCP.

Vehicular networks have the mobility of nodes as its intrinsic characteristic. At each instant of time, active nodes roam from one intersection to another, switching from covered areas to uncovered ones, making the coverage problem even more challenging since we must take into account the direction and speed of each node. MCP-Greedy does not take into account this peculiarity, focusing its attention on the definition of a mechanism for the dissemination of information using only one shot, maximizing the amount of nodes reached by a single message. By dealing only with the instantaneous concentration of nodes at each intersection, MCP-Greedy has the potential to provide lower quality results than PMCP, because MCP-Greedy does not take into account the movement of vehicles.

Major cities count with roads that serve as access corridors as they concentrate a significant percentage of traffic. Because MCP-Greedy is not aware of the direction of the vehicles, this heuristic can (for example) suggest the deployment of dissemination points very close to each other, resulting in wasted or redundant equipment, since the same vehicle will receive the same information twice whereas others will be left without any information.

PMCP

A snapshot of the traffic is not adequate to fully represent all the aspects of a mobility model. This section presents PMCP, a probabilistic version of the Maximum Coverage Problem. The probabilistic model is useful to reduce biases in the data, at the same time it represents an efficient alternative to incorporate the urban mobility model within any vehicular trace. The core of the probabilistic model is the stochastic matrix $M_{r1,\, r2}$, where *r1* and *r2* are two roads that intersect. The value $M_{r1,\, r2}$ indicates the probability that a vehicle travelling on road *r1* stays on this road when *r1* intersects *r2*. Each of its entries is a nonnegative real number representing a probability.

The probability matrix is one of the inputs of PMCP and we assume that it can be obtained from applications like Waze (2008) or even that it can be measured by the transit authority using road sensors, observation, or estimated based on road characteristics like length, location, frequency of congestions, maintenance cost per mile, etc.

The Probabilistic Maximum Coverage Problem can be stated as:

Definition 1 (Probabilistic Maximum Coverage Problem)

Suppose a set V={v_1,v_2,...v_n} of n elements, a collection C={c_1,c_2,...,c_k} of k subsets of V and a matrix P of size n×k where each P_{xy} gives the probability that element v_x in c_y for all x in {1,2,..,n} and for all y in {1,2,..,k}. Select l subsets from C such that their union has the maximum expected cardinality.

The probability matrix allows PMCP to encode a static mobility model enabling the projection of the vehicles flow over time. PMCP assumes that:

(i) Each traffic information (message) can be sent multiple times, as long as the information is still helpful to the vehicles. Any vehicle that reaches a covered intersection in a time such that the information is still useful will benefit from the message and the dissemination system will have done the job.

(ii) Vehicles are in constant motion, roaming from covered to uncovered intersections. If a vehicle has a probability *p* of driving-through a covered intersection, than the vehicle can be considered to be covered with probability *p*.

(iii) The system does not know the future positions of the vehicles, but it knows the collective behavior. For every intersection, the system knows the percentage of vehicles that continue on the road (or turn into any other).

PMCP receives as input:

M: Matrix of intersections of size *r* × *r*, where *r* represents the quantity of roads in the region under study. Each $M_{i,j}$ holds the amount of vehicles in the intersection of roads *i* and *j*.

α: Maximum quantity of dissemination points that can be deployed.

P: Probability matrix of size *r* × *r* where each P*i,j* holds the percentage of vehicles that continue on road *i* at the intersection *(i,j)*.

Algorithm 2 PMCP

Input: M, α, P;
Output: Selected intersections to receive DP;

```
 1: Sol ← ∅; {solution set starts empty}
 2: Quant ← 0; {no intersection selected yet}
 3: Cover ← 0; {no coverage}
 4: ∀i, j do C_{i,j} = GetProjectedFlow(i, j, M, P);
    {coverage of each intersection takes into account the probability of remote vehicles
    to drive-through the intersection}
 5: while Quant < α and Exists Uncovered Vehicles do
 6:     Select Max C_{i,j}; {intersection with more vehicles}
 7:     Sol ← Sol ∪M_{i,j}; {add intersec to solution}
 8:     Cover ← Cover + C_{i,j}; {update coverage}
 9:     Quant ← Quant + 1; {increase quantity of intersections}
10:     Remove Max C_{i,j} and Max M_{i,j}; {remove selected intersection}
11:     ∀i, j do C_{i,j} = GetProjectedFlow(i, j, M, P);
12: end while
13: return Sol, Cover;
```

Algorithm 2.

PMCP is shown in Algorithm 2. From lines 1 to 3 the heuristic initializes variables. The set *Sol* starts empty and variables *Quant* and *Cover* start as zero. Line 4 projects the flow to find the coverage $C_{i,j}$ at each intersection *(i,j)*. This step is the core of our approach and it is detailed in next subsection. From lines 5 to 12, the heuristic loops selecting (at each iteration) the set (intersection) that offers the maximum projected coverage (line 6). The selected intersection is added to the set *Sol* (line 7). The variable *Cover* is increased with the coverage of vehicles achieved in the selected intersection $C_{i,j}$ (line 8). The *Quant* of dissemination points is incremented (line 9) and the selected intersection is removed from the data (line 10). PMCP loops until it reaches the limit of α dissemination points deployed or it has covered all vehicles (stop condition in line 5).

It is easy to notice that PMCP differs from the Greedy MCP just in the strategy used to compute the coverage. However, computing the coverage is just what leads to the success of the strategy since that parameter defines where the next dissemination point is going to be deployed.

Next subsection explains how PMCP uses the probabilistic model to compute the volume of vehicles at each intersection.

Projecting the flow

The projection is computed analysing the number of vehicles at each intersection, and the probability of each vehicle to stay on its actual road, or leave it.

Equation 1 computes the coverage of vehicles moving left-to-right on road *i* towards $M_{i,j}$. The function *UncoveredVehicles()* returns the quantity of vehicles still not covered in a given intersection, and the product computes the compound probability resulting from the series of intersections.

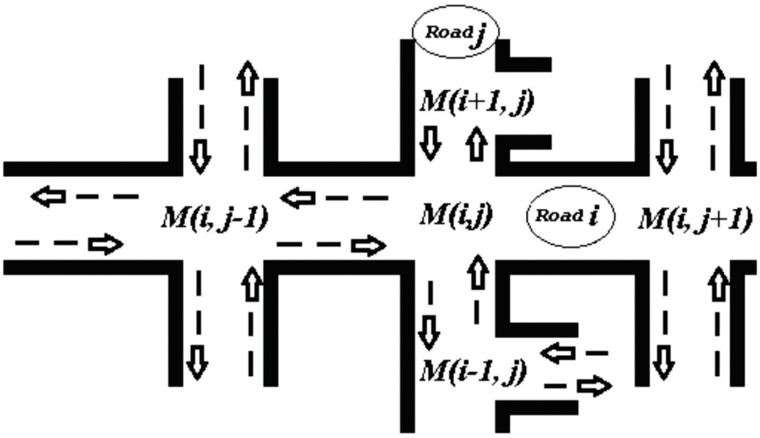

Figure 1. Projecting the flow.

$$LR_{i,j} = \sum_{k=0}^{j-1} (UncoveredVehicles(M_{i,k}) \cdot \prod_{l=k}^{j-1} P_{i,l}) \quad (1)$$

Equation 2 computes the coverage of vehicles moving right-to-left on road i.

$$RL_{i,j} = \sum^{\forall k > j} (UncoveredVehicles(M_{i,k}) \cdot \prod_{l=j+1}^{k} P_{i,l}) \quad (2)$$

Equation 3 computes the coverage of vehicles moving bottom-up on road j.

$$BU_{i,j} = \sum_{k=0}^{i-1} (UncoveredVehicles(M_{k,j}) \cdot \prod_{l=k}^{i-1} P_{j,k}) \quad (3)$$

Equation 4 computes the coverage of vehicles moving top-down in Figure 1 on road j. The quantity of vehicles arriving from intersections $M_{i+1,j}$, $M_{i+2,j}$, ... , that reaches $M_{i,j}$ is:

$$TD_{i,j} = \sum^{\forall k > i} (UncoveredVehicles(M_{k,j}) \cdot \prod_{l-i+1}^{k} P_{j,k}) \quad (4)$$

Therefore, the total projected flow ($PF_{i,j}$) can be computed by adding $LR_{i,j}$, $RL_{i,j}$, $BU_{i,j}$ and $TD_{i,j}$ to the quantity of uncovered vehicles found in intersection $M_{i,j}$, as stated in Equation 5.

$$PF_{i,j} = UncoveredVehicles(M_{i,j}) + LR_{i,j} + RL_{i,j} + BU_{i,j} + TD_{i,j} \quad (5)$$

Next section shows the experiments and results of this research.

Experiments and results

We developed a set of tools, including a generator of graphs and a traffic simulator. The generator of graphs defines random sets of roads in Manhattan-style. Each road has a capacity and a direction (one-way or two-ways). The generator creates junctions among these roads and exports the scenario to the traffic simulator. The traffic simulator executes r^2 cycles of traffic lights, where r is the amount of roads. In every cycle, the simulator adds new vehicles at the beginning of each road using the Distribution of Poisson with λ=*RoadCapacity*. When vehicles reach the borders of the region, they leave the simulation. After all cycles performed, we apply PMCP and Greedy MCP.

This experiment considers one hundred random scenarios in a Manhattan-style topology. We change the capacity (λ) of each road using different seeds in order to generate various configurations of roads. We graph the mean and standard deviation obtained for the coverage. The asymptotic confidence interval of 95% was computed to the coverage, presenting values close to zero. Figure 2 shows the mean coverage obtained for PMCP and Greedy MCP.

The y-axis represents the mean percentage of the vehicles covered. The x-axis shows the amount of dissemination points deployed along the region. Note that the amount of dissemination points is shown as a ratio between the total number of intersections and the amount of intersections receiving dissemination points.

PMCP outperforms the Greedy MCP. Greedy MCP uses static volume of vehicles to locate the dissemination point, while PMCP uses the dynamic volume. Greedy MCP selects always the intersection able to cover the greatest number of vehicles not yet covered. On the other hand, PMCP chooses the intersection that receives the highest expected flow of vehicles considering the movement of each vehicle.

The standard deviation of the coverage is shown in Figure 3, with a variation less than 2.2% points, indicating some sort of stability for different scenarios for both heuristics. So, PMCP is able to improve the coverage ratio, while preserving the same deviation than Greedy MCP. The results show that PMCP slightly changes the position of some dissemination points (moving a dissemination point a few intersections away), and this new configuration of dissemination points results in better coverage. PMCP performs better because it takes into account the vehicles mobility. Further study is required to understand the performance of PMCP across heterogeneous urban topologies.

Conclusion

In this paper we address the problem of locating dissemination points in a Manhattan-style topology. We propose a probabilistic heuristic that selects the intersections that offer the maximum projected flow. Computing the projection of the flow requires as input (i) the number of times that each intersection has been crossed and (ii) the turning matrix.

The number of times that each intersection has been crossed tells us about its popularity.

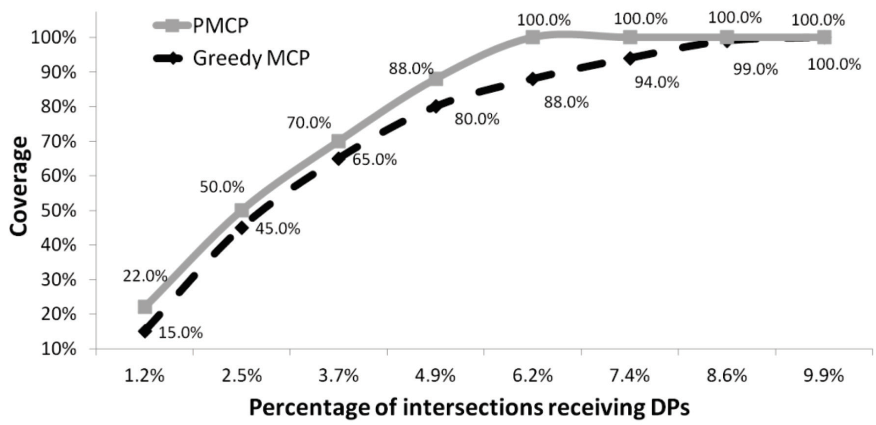

Figure 2. Coverage × percentage of intersections with dissemination points.

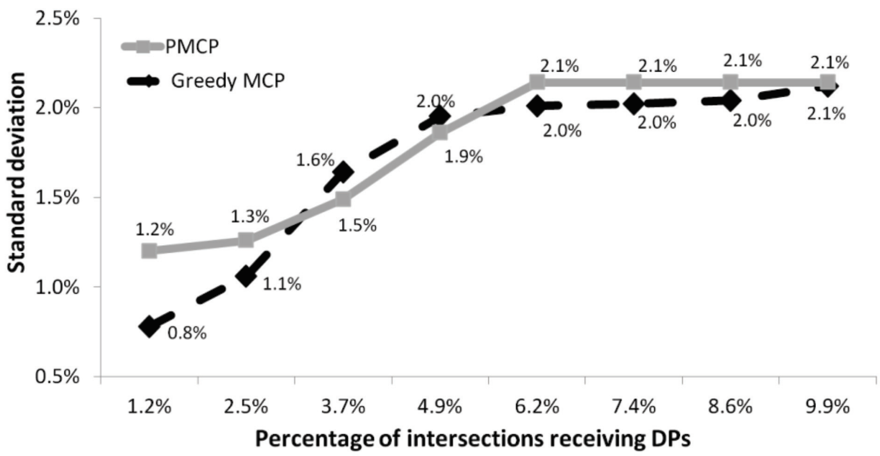

Figure 3. Standard Deviation (of coverage).

On the other hand, the turning matrix gives us a summarized view of urban displacements. Recall that the turning matrix returns the driver's preference when facing the junction of two (or more) roads.

Our vision is that bringing together the popularity matrix and the turning matrix would result in better allocation of dissemination points. Vehicular networks have the mobility of nodes as an intrinsic characteristic. At each instant of time, active nodes roam from one intersection to another, switching from covered areas to uncovered ones, making the coverage problem even more challenging.

MCP-Greedy does not take into account this peculiarity, focusing its attention on the definition of a mechanism for the dissemination of information using only one shot, maximizing the amount of nodes reached by a single message. By dealing only with the instantaneous concentration of nodes at each intersection (in a moment of time), MCP-Greedy may provide results below to a heuristic that takes into account the movement of vehicles. The probabilistic model improves the strategy to select intersections, ensuring higher coverage with less dissemination points. In our simulated scenarios (always in Manhattan topology) we were able to achieve almost 100% of coverage through the deployment of dissemination points in less than 7% of the intersections using PMCP, while MCP-Greedy requires 8.6% of the intersections to achieve similar coverage.

Although PMCP shows better results, more research is required to fully comprehend the pros and cons of this technique. Our team is particularly interested in understanding: (i) How PCMP affects the coverage pattern of the region; (ii) Whether the vehicles drive-through less/more PMCP-dissemination-points during a typical trip; (iii) Whether PMCP improvements also occur over non-grid topologies.

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