Realtime Predictive Patrolling and Routing with Mobility and Emergency Calls Data

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Abstract

A well-planned patrol route plays a crucial role in increasing public security. Most of the existing studies designed the patrol route in a static manner. Situations when rerouting of patrol path are required due to the emergencies, e.g., an accident or ongoing homicide, are not considered. In this paper, we formulate the crime patrol routing problem jointly with dynamic crime event prediction, utilising crowdsourced check-in and real-time emergency call data. The extensive experiment on real-world datasets verifies the effectiveness of the proposed dynamic crime patrol route using different evaluation metrics.

Introduction

Police patrols play an important role to establish and ensure public safety. However, police resources are much more limited than the operational demands. This, therefore, requires an efficient patrol path generation for the police officers. Traditionally, police patrols in random routes to mitigate the crime risks. Random routing makes the chances lower in ensuring the presence of a police officer during a crime event. Therefore, many researchers considered the crime hotspots in patrol route planning to direct the police officers (Chawathe 2007; Chevaleyre, Sempe, and Ramalho 2004; Li et al. 2011). Although, such route plannings are based on the static environment while the environment changes constantly. Few algorithms were developed in the past to design optimal police patrol routes in a dynamic environment (Chen and Yum 2010; Chen 2012). However, many of these works did not consider the dynamic human activities in the urban environment that can influence crime patterns and were designed mostly using static and simulated data rather than real-time real-world sensor data.

In this paper, we formulate the patrol route planning problem to deal with the coordination of police officers from visiting the time-dependant crime hotspot areas to prevent crime event occurrences and from attending real-time emergencies. We leverage human movements, i.e., location-based social network check-ins data, as sensor information to better predict crime hotspots in the next time interval. Understanding human mobility data plays an important role in recommendation service to planning in cities (Sadri et al. 2018). Fusing human mobility data with other data, we generate the prediction probability of crime hotspot in areas of interests. Finally, we use the prediction result to generate an initial patrol strategy. The route is continuously refined based on real-time demand from emergency calls data. Two goals are set to accomplish the task which include minimizing the crime risk of an area in a time interval and minimizing the time of traveling. In summary, the contributions of this paper are:

1. A new problem formulation for dynamic police patrolling route planning, combining crime event prediction using human mobility and real-time incident response.
2. A newly proposed greedy algorithm based on the prediction and priority of the emergency call for a single police officer.
3. New evaluation methodologies and metrics to evaluate the problem, demonstrated on extensive experiments using real-world data.

Related Work

In (Chevaleyre, Sempe, and Ramalho 2004; Chawathe 2007), the authors focused on road network topology to propose an optimal patrol route. A cross entropy based method was applied to provide randomness in patrol route selection in (Li et al. 2011). The authors considered the spatial pattern of crime hotspots to suggest patrol routes and the effectiveness of collective patrol activities. However, the proposed patrol routes in these works considered the patrol environment static. In (Rahaman et al. 2017), the authors used accessibility contexts to suggest path with minimal travel time. However, the contexts are non dynamic in this problem.

In (Chen and Yum 2010; Chen 2012), the authors applied a cross entropy based method for a single patrol unit and an approximate cross entropy method for a patrol team to identify the patrol route dynamically. The authors proposed dynamic solutions for parking officer to increase the probability to catch maximum cars in violation in (Shao et al. 2018; 2016) and extend their problem for multiple parking officers in (Qin et al. 2019). Some researchers proposed metaheuristic approaches to solve orienteering problems that are constrained by time (Mei, Salim, and Li 2016). But, these works did not consider predictive analytics in conjunction with optimization. Few researchers considered the predictive analysis of crime events and demands into patrol area allocation task (Leigh, Dunnett, and Jackson ; Mukhopadhyay et al. 2017). These works mainly focused on positioning the police officers into different areas to maximize the demand coverage instead of generating patrol route. None of the mentioned work optimizes the patrol path generation considering the fluctuation in crime event occurrences and sudden emergency call that need to be attended by a patrol officer.

Preliminaries

In this section, we describe the Patrol Route Planning System in a dynamic environment.

Patrol Nodes. We assume that the Patrol Route Planning System consists of different patrol nodes, $v_i \in V$. Each node represents a 400×400 grid of a police beat and associated with three variables, crime density, crime arrival rate, and priority.

w_i denotes the crime density of a certain node in $v_i \in V$. It is calculated based upon the number of crime events at node v_i during time interval, t in the past 30 days. $\lambda_i(t)$ denotes the crime arrival rate in a node, v_i during the t time interval. It is calculated based on the crime event trend of next 7 days during a time interval, t. The priority of each node, p_i varies from 1 to 5. 5, means the highest priority. It is set to 1 initially.

Patrol Network. A directed weighted graph, $G(V, E)$ is considered for the patrol network. Here V represents the patrol nodes, and E represents the edges between the nodes. The travel time between nodes represents cost, C, which are associated with the edges between the nodes. The solution of the crime patrol route system, S is a set of edges. It can be represented as follows:

$$e_{ij} = \begin{cases} 1, & \text{if there is path between node i and j.} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

Hotspot Nodes. Hotspot nodes, $N \subseteq V$ represent the patrol nodes which are predicted as hotspots for a planned interval, T. T is the total duty hour that a police officer serves in a day. A police officer generally spends 11-15 minutes in each hotspot location (Koper 1995). This is represented as dwell time, $a(n_i)$.

Emergency Situations. M is a set of emergency nodes that a police officer is required to visit based on real-time demand. $M \subseteq V$. It is empty initially. When an emergency happens in a node, that node is entered in this set. As a certain crime event is happening in such nodes, the crime density, w_i, and crime arrival rate, λ_i is set to 1 for such type nodes. The priority of these nodes changes based on the type of call (Brown 2006).

Problem Formulation

In this section, we formalize the problem of planning the patrol route effectively in a dynamic environment. It comprises two components: crime event prediction and patrol route planning.

Crime event prediction component aims to predict crime event in a short-term interval. The patrol route planning problem in a dynamic environment can be described as: *Find a patrol route that maximizes the patrol rewards in minimum cost (here, time is the cost metric).*

L is a set of all nodes appeared in hotspot node, N and emergency node, M which a police needs to visit. Hence, $L = N \cup M$. Mathematically, the patrol reward for each node, l_k during time interval, t can be calculated as

$$B(l_k(t)) = exp(w_k(t)) * p_k * \lambda_k(t). \tag{2}$$

Here, $w_k(t)$ denotes the past 30 days crime density in node, k during t time interval. p_k is the priority of crime event and $\lambda_k(t)$ represents the trend of crime. The intuition behind equation 2 is crime usually happens in the vicinity of past crime which has been represented by w. The presence of police officer in high crime areas reduce crime rates significantly (Sherman and Weisburd 1995). $exp(w)$ has been used to emphasize this value. To consider the impact of the priority of the crime event, p has been considered in the equation. Incidents priorities are important in response optimization (Mukhopadhyay et al. 2017). $\lambda_k(t)$ models the trend of crime events in node, k during time interval, t. Our goal is to maximize this reward for a police officer during the planning horizon. Mathematically, the goal is

$$max \sum_{t \in T} \sum_{l_k \in L} B(l_k(t)) \tag{3}$$

s.t.,

$$\sum_{e_{ij} \in S, l_j \in L} C(e_{ij}) + a(l_j) \leq T \tag{4}$$

$$t_a = t_c + C(e_{l,l+1}) \tag{5}$$

$$t_a \in t, l_k \in N \tag{6}$$

In the first constraint, Equation 4, T represents the maximum time cost which is the planning horizon. It denotes that the time cost between travelling node i to j and the dwell time, $a(l_j)$ in node, j can not exceed the maximum time cost. In second constraint, Equation 5, t_a represents the time when a police may arrive in next node. t_c denotes the current time when the next planning start. The third constraint, Equation 6 limits the repeated hotspot visits in prediction interval. In each interval new hotspots are predicted. Before each planning iteration, the current visited node is removed from N and M and V is updated accordingly. It prevents visiting same nodes repeatedly.

System Approach

In this Section, we describe the short-term crime prediction method and the prediction based dynamic greedy algorithm to design police patrol route.

Crime Event Prediction

We extract several features as predictors of crime event prediction model, including historical features, geographic features, and mobility features from crime history and foursquare check-in data. For node v_i at time interval t, we measure 30-days and 7-days crime event density as historical features from historical crime data, venue category density, venue category distribution, and regional diversity as geographic features from foursquare venue data. We extract visitor entropy, visitor homogeneity, visitor ratio, user count and observation frequency from foursquare check-in data as dynamic features (Rumi, Deng, and Salim 2018a; 2018b). Finally, we train a Random Forest (RF) algorithm to predict hotspot nodes in the next time interval. We choose RF as a classifier algorithm because the non-parametric nature makes the algorithm good fit classifier in heterogeneous and multidimensional feature space (Kadar and Pletikosa 2018).

Patrol Route Planning Algorithm

Here, we describe the Greedy algorithm, Greedy (DWP) for finding the optimal path solution for police patrol route. The objective of this algorithm is to find the path which can collect most reward throughout the duty time of a police officer in minimum travelling. The algorithm is described in Algorithm 1. Here, T_s denotes the start time of patrol and T_e denotes the end time. Cost(S) is calculated based on the sum of traveling time between a current node to the next node and average dwell time of a police officer. There are two operations callImportance (V) and update (V). They are described below:

callImportance (V): This function returns the importance of each patrol node. The node which returns the highest reward is considered most important. It also depends on the distance from the current node of the police officer. Hence, the importance of patrol nodes is calculated using the Equation 7.

$$Importance(v_i(t)) = B(v_i(t))/Cost(v_c, v_i). \quad (7)$$

update (V): After each iteration of adding the node with the highest importance into solution, the node information is updated with the latest information of 911 emergency response incidents. The information of potential crime hotspots is updated in every 2-hours based on dynamic crime event prediction.

Datasets

The datasets are collected for two different police beats, K2, and E2 in Seattle, USA.

Crime Dataset The crime event records of Seattle, USA from “03-2012” -“02-2013” are collected from public source (Sea b). The total number of crime events that happened in K2 police beat during this period was 1245, and in E2 police beat, this number was 1649.

Check-in Data We collect foursquare venue data and check-in data in Seattle for the same period as crime event records from the authors (Yang, Zhang, and Qu 2016; Yang et al. 2015). For the K2 police beat, the data set consists of 3784 check-ins performed by 746 users in 698 venues and in E2 police beat, 500 users performed 4709 check-ins in 754 venues during the same period as crime dataset.

Algorithm 1 Algorithm for Prediction Based Dynamic Greedy Solution

Input: a given graph $G = (V, E)$
a set of potential next nodes, V
A set of constraints among the variables
Output: A solution, S
Initialisation : $S = \emptyset$
$T_s = 480$
$T_e = 1200$
$T_s \leq T \leq T_e$
while $Cost(S) < T$ **do**
  if (V has no Incident Record) **then**
    add a Null to S
  else
    callImportance (V)
    add v_i with highest importance to solution, S
  end if
  update (V)
end while

911 Incident Response To simulate the emergency call to respond, we use 911 Incident Response data (Sea a). In K2 police beat, 9855 emergency calls were attended by police officers during the same period as crime data. In E2 police beat, this number was 5821.

Experiments

We evaluate the greedy based solution in this section, followed by the description of evaluation metrics and comparison algorithms.

Data Preparation

For the crime event prediction, a day is partitioned into intervals of 2 hours. We use data that lies into “04/2012 - 12/2012” for training purpose. The data lies in “01/2013 - 02/2013” are used to predict crime and design the patrol route. We conduct the experiments by assuming that a police officer starts his duty at 8 am and ends at 8 pm. We also assume that the police officer starts patrol duty from grid 1.

Evaluation Methodology

The evaluation metrics determine patrol reward by a police officer. We propose three different metrics to evaluate the solution : *efficiency*, *robustness* and *idle time*.

Efficiency The efficiency measurement calculates the fraction of crime events which have been successfully prevented by a police officer during his duty hour. The effeciency value returns 1 if a police officer visits the hotspot node in between before or after 1-hour of the occurrence.

Robustness The robustness determines how quickly a police officer responds to an emergency call based on the priority of the call. The robustness value based on crime type is noted in Table 1. It is determined based on the arrival duration after making the call and the priority of the crime type (Brown 2006).

Idle Time Idle time determines the amount of time that a police officer can have as a break instead of visiting the unproductive path. The idle time of a day is calculated in a

Table 1: Robustness calculation based on arrival time

Arrival Time (min)	Priority of Call				
	5	**4**	**3**	**2**	**1**
< 15	1	1	1	1	1
[15 - 30]	0	0	1	1	1
[31 - 60)	0	0	0	1	1
> 60	0	0	0	0	1

minute using the following equation.

$$IdleTime = \sum_{t_m=T_s}^{T_e} t_m(S = \emptyset) \tag{8}$$

Here, T_s and T_e represents start and end time of patrol respectively.

Comparison Algorithms

Our proposed algorithm is a greedy method which combines the prediction output and real-time emergencies. We set two benchmarks of the greedy algorithm, Static Greedy Algorithm (Greedy (S)), Dynamic Greedy without Prediction Algorithm (Greedy (DWOP)) and Hamilton algorithm to compare our method. In Greedy (S), the incident records associated with each node, V depends on only the history of crime events in that node. It does not change the route plan based on a dynamic emergency call. In Greedy (DWOP), we consider the dynamic arrival of emergency call. However, no prediction method is applied in this algorithm. In Hamilton algorithm, the hamilton path is generated based on the hotspot and emergency call nodes in every 2-hour.

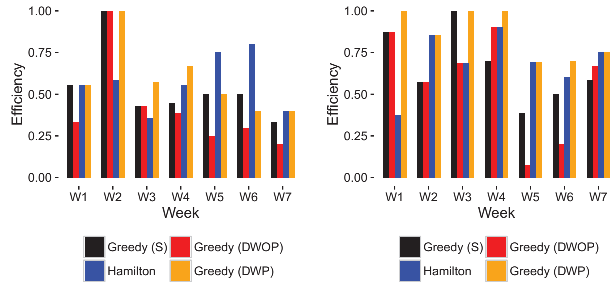
Performance Results

In this Section, we demonstrate the average weekly performance result that a police officer can achieve during his duty hours using three different greedy algorithms, *Greedy (DWP)*, *Greedy (DWOP)*,*Greedy (S)* and Hamilton algorithm in K2 and E2 police beats.

Efficiency The efficiency result for K2 and E2 police beats are illustrated in Figure 1 for different weeks. We observe that the efficiency value using the solution by Greedy (DWP) is higher than the solutions by Hamilton, Greedy (DWOP) and Greedy (S) in E2 police beat. In K2 police beat, the solution by Greedy (DWP) provides higher efficiency value than others in most of the weeks.

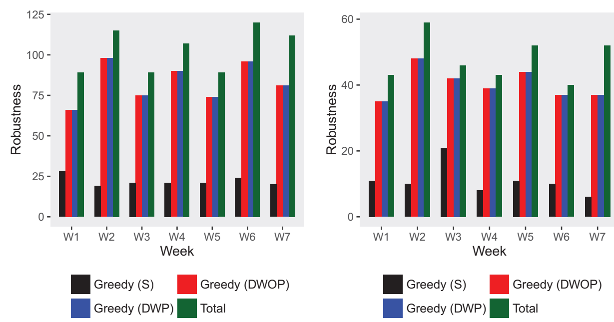
Robustness The weekly sum of robustness value for E2 and K2 police beats in Seattle are shown in Figure 2. We can observe that the solutions provided by dynamic greedy algorithms, Greedy (DWP), and Greedy (DWOP) achieve the highest robustness value in every week in both regions.

Idle Time The average idle times (minutes) that a police officer can have during his duty time for each day in a week are illustrated in Table 2. It shows that Greedy (DWOP) and Greedy (S) provide solutions which include no idle time for a police officer. On the opposite, a police officer can have a good amount of idle time by patrolling the path generated from Greedy (DWP) and Hamilton algorithm.



(a) K2 Beat (b) E2 Beat

Figure 1: Efficiency of solution in different beats



(a) K2 Beat (b) E2 Beat

Figure 2: Robustness of solution in different beats

Table 2: Idle time in different beats

Week	Idle Time					
	k2 Beat			E2 Beat		
	Greedy (DWP)	Greedy (DWOP) and (S)	Hamilton	Greedy (DWP)	Greedy (DWOP) and (S)	Hamilton
W1	177.43	0.0	132.86	291.29	0.0	308.0
W2	129.14	0.0	105.14	272.14	0.0	285.29
W3	162.57	0.0	131.86	298.0	0.0	287.71
W4	134.86	0.0	106.43	302.43	0.0	333.29
W5	140.29	0.0	127.43	272.00	0.0	299.43
W6	135.85	0.0	125.71	225.00	0.0	284.43

Conclusion

This work focuses on designing police patrol route considering dynamic changes in the environment. Here, human mobility is considered as an environmental sensor to determine the next potential hotspot nodes. The proposed greedy algorithm is also responsive to real-time emergencies. The performance results illustrate that the proposed model is efficient in preventing crime events and robust to emergency situations comparing with two different versions of greedy algorithms and hamilton algorithm using three meaningful evaluation metrics.

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