Towards Optimal Police Patrol Routes with Genetic Algorithms

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Abstract. It is quite consensual that police patrolling can be regarded as one of the best well-known practices for implementing public-safety preventive policies towards the combat of an assortment of urban crimes. However, the specification of successful police patrol routes is by no means a trivial task to pursue, mainly when one considers large demographic areas. In this work, we present the first results achieved with GAPatrol, a novel evolutionary multiagent-based simulation tool devised to assist police managers in the design of effective police patrol route strategies. One particular aspect investigated here relates to the GAPatrol's facility to automatically discover crime hotspots, that is, high-crime-density regions (or targets) that deserve to be better covered by routine patrol surveillance. In order to testify the potentialities of the novel approach in such regard, simulation results related to two scenarios of study over the same artificial urban territory are presented and discussed here.

1 Introduction

Police patrolling is an important instrument for implementing preventive strategies towards the combat of criminal activities in urban centers, mainly those involving violence aspects (such as bank robbery, theft, armed robbery, gang fighting, drug dealing, environmental degradation, and kidnapping). An underlying hypothesis of such preventive work is that, by knowing where the occurrences of crime are currently happening and the reasons associated with such, it is possible to make a more optimized distribution of the police resources available to control the overall crime rates.

In fact, place-oriented crime prevention strategies have been the focus of much research study in the last decades, centering, in a way or another, on the concept of "crime hotspots" [3][6]. The main point argued in this theory is that crime is not spread evenly across urban landscapes; rather, it clumps in some relatively small places (that usually generate more than half of all criminal events) and is totally absent in others. Hotspots refer to those high-crime-density areas (targets) that deserve to be better controlled by routine patrol surveillance or other more specific police actions.

Usually, the discovery and analysis of such hotspots are done iteratively by the construction of visual maps, which allow the association of the types of hotspots with

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their crime patterns and possible police actions. Moreover, simple-to-apply statistical tests can reveal a prior understanding of what should be expected to be found in a hotspot map, even before the map has been created. Tests for clustering are particularly important. However, analysts may waste valuable time in their attempts to create a crime hotspot map if a test fails to reveal that some clusters (hotspots) exist in the analyzed data. Indeed, different mapping and statistical techniques have revealed the different applications to which they are suited and demonstrated that they have pros and cons with respect to the mapping outputs/results they generate. One consensus that has emerged in this sense is that identifying hotspots requires multiple complementary techniques, since no single method is good enough for all circumstances.

With this in mind, in this paper, we present GAPatrol, a novel evolutionary multiagent-based simulation tool devised to assist police managers in the design of effective police patrol route strategies. As the specification of these patrol routing strategies is intimately associated with the discovery of hotspots, our claim is that such decision-support tool provides an alternative, automatic means for the delimitation and characterization of important crime hotspots that may exist or appear over a real demographic region of interest. The conceptualization of GAPatrol was directly inspired by the increasing trend of hybridizing multiagent systems (MAS) [7] with evolutionary algorithms (EAs) [1], in such a way as to combine their positive and complementary properties [5]. Moreover, it correlates with other prominent research studies that have recently been conducted in the public-safety domain by making use of the theoretical/empirical resources made available by multiagent-based simulation systems [2][4].

In order to testify the potentialities of the GAPatrol approach in uncovering crime hotspots, simulation experiments related to alternative scenarios of study over the same artificial urban territory have been conducted, and some preliminary results are presented and discussed in the following. This is done after characterizing the entities comprising the simulated urban society in focus and some configuration issues related to the adopted multiagent simulation environment, as well as briefly conveying some important details about the evolutionary engine behind GAPatrol.

2 GAPatrol

The entities that take part in our simulated multiagent society are described as follows. There is a set of $NP = 6$ police teams available, each one associated with a patrol route passing through some special locations of the urban territory considered. There is no distinction, in terms of skills, between the police officers allotted to the different police teams. We also assume that the teams patrol intermittently and the speed of their patrol cars are the same, meaning that the time spent by a given team in a given location will depend solely on the size of its route. However, routes can overlap and/or share common points of surveillance. The special locations to be patrolled are referred to here as targets, which can be differentiated with respect to the type of commercial/entertainment establishment they represent (like drugstores, banks, gas stations, lottery houses, squares, and malls). In all, there are $NT = 41$ targets in the territory.

Besides, there is a set of $NC = 15$ criminals representing the actors that frequently try to commit the crimes. Each criminal is endowed with a limited sight of the environment, measured in terms of grid cells. For instance, with a vision of 1,000 meters, if each cell has 100-meter sides, the radius of the criminal's sight will be 10 square cells around him/herself. We assume that there is no chance of having a criminal being arrested and jailed, meaning that the number of criminals is always constant. Each criminal offender has a personality, which, in turn, determines the types of places he/she more frequently selects as targets for committing crimes. Moreover, the personality can vary over time, passing from novice to intermediate to dangerous, according to the success of the criminal in committing crimes. For each pair (type of personality, type of target), there is a certain probability for committing a crime, as showed in Table 1. The underlying logic is that a dangerous criminal has a higher probability to seek out banks than a novice, for instance, aiming at obtaining higher returns in money and due to his/her higher level of expertise.

Table 1. Probability of approaching a target for different types of criminal personalities

	Square	Drugstore	Lottery	Gas Station	Mall	Bank
Novice	50%	30%	20%	0%	0%	0%
Intermediate	20%	30%	30%	20%	0%	0%
Dangerous	10%	15%	15%	10%	15%	35%

Having probabilistically selected the next type of target, it is assumed that the criminal has the knowledge necessary to localize the closest exemplar target on the map, moving straight towards such point. The time expended to reach the target is calculated based on the speed of the criminal and the distance to the target. The shortest period of motion, considering all *NC* criminals, is taken as a reference, so that the criminals are allowed to move only during this time period. Finally, the decision whether or not to commit a crime is made based on the existence of one or more police teams within the radius of the criminal's sight. If the offender decides to not commit a crime, then he/she will select a new target to approach, leaving the current location. Otherwise, we assume that a crime will be simply committed.

GAPatrol's multiagent engine runs atop the Repast simulation environment [2]. Each set of routes designed by a GAPatrol chromosome (see below) gives rise to a series of simulation executions in order to evaluate the crime prevention performance of such set of routes. Each simulation instance runs 3,000 ticks, which would roughly correspond to one month of real-life events.

The evolutionary engine of GAPatrol is based on Genetic Algorithms (GAs) [1], a metaheuristics that complies with the Darwinian theory of evolution by natural selection to efficiently design (quasi-)optimal solutions to complicated search problems. Such metaheuristics maintain a population of individuals, which represent plausible solutions to the target problem and evolve over time through a process of competition and controlled variation. The more adapted an individual is to its environment (i.e., the solution is to the problem), the more likely will such individual be exploited for generating novel individuals. In order to distinguish between adapted and non-adapted individuals, a score function (known as fitness function) should be properly specified beforehand in a manner as to reflect the main restrictions imposed by the problem.

In this paper, a customized GA model is employed for the design of effective police patrol routing strategies, making direct use, for this purpose, of the multiagent engine described earlier. Due to the dynamism implied by the criminals' non-deterministic behavior, this may be viewed as a challenging problem to be coped with by GAs. In what follows, we describe the main components of the GAPatrol evolutionary engine.

Each individual in the evolutionary process represents a set of patrol routes, each route associated with a given patrol team. By this way, the number of routes is pre-fixed. However, the length of each route and the targets it may include are defined adaptively, therefore allowing the overlapping of routes through the crossing of their sub-routes or through the sharing of targets. There is no need that a target be covered by at least one route, which means that the evolutionary process is free to concentrate on those targets that seem to deserve better police patrolling attention (hotspots), if this might be the case. Each individual should be interpreted as a sequence of pairs of indices, the first one representing a police team and the other referencing a target. A binary codification of the chromosomes is employed for such purpose.

As the main objective of this study is to find a set of patrol routes that minimizes the number of crime occurrences in a given area, a straightforward fitness function that was adopted for the evaluation of the individuals is the inverse of the number of crimes. This fitness function is further modified by a fitness scaling mapping operator, so as to better discriminate between the individuals' capabilities and to prevent the premature convergence problem [1]. In each execution of GAPatrol, the initial population of route sets is randomly created according to a uniform distribution over the values of all genes (i.e., bits of the individuals). The fitness value of each individual is calculated taking as basis the average number of crimes achieved in $NS = 10$ executions of the multiagent engine. After that, according to the roulette wheel selection operator [1], some individuals are recruited for mating (via the crossover operator) and producing offspring. The latter may serve as targets for the simple mutation operator. Finally, the current best individuals (from both parents and offspring) are selected deterministically for comprising the next GAPatrol's generation. This process is repeated until a stopping criterion is satisfied, namely that a certain number of generations are reached. Then, the best individuals (sets of patrol routes) produced across all generations are presented to the police managers as the (quasi-) optimal solution to the considered simulation scenario, allowing them to provide visual analysis of the characteristics underlying these most effective sets of patrol routes and the hotspots they have discovered.

3 Results and Discussion

In order to evaluate the performance of the GAPatrol approach while tackling the problem of hotspots localization, some simulation experiments were carried out and their results are briefly presented here having as basis two distinct scenarios defined over a simulated urban environment that mimics a well-known neighborhood of Fortaleza, Brazil. In such study, the GA metaparameters were set arbitrarily as follows [1]: 95% as crossover rate, 5% as mutation rate, population size of 30 individuals, and 100 as the maximum number of iterations. Since the criminals begin the simulations as novices, the points that should be targeted more frequently by them are drugstores, squares, and lotteries. Figure 1 presents the physical disposition of all 41 targets over the environment as well as the points of departure of the criminals in the two scenarios. The first scenario was devised as a controlled scenario where the points of departure were localized strategically in the middle of the four quadrants of the environment, facilitating in the recognition of the hotspots. Conversely, in the second scenario, the criminals start out from a unique source, forcing them to initially roam out around the area, which leads to a more dispersed distribution of the hotspots.

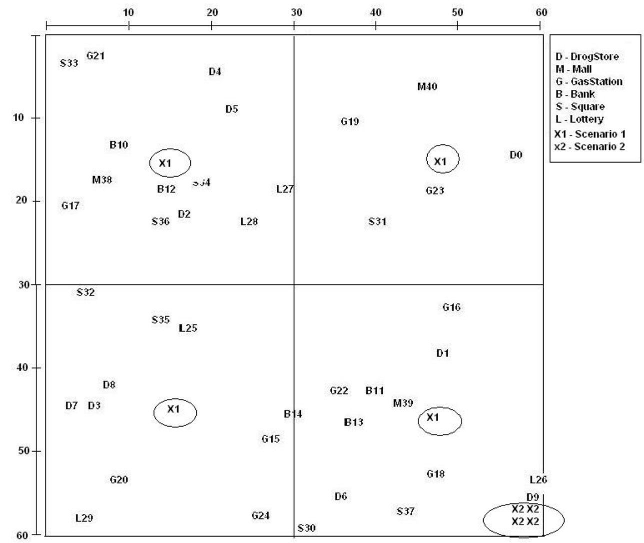

Fig. 1. Physical location of the targets (in terms of grid squares) and points of departure of the criminals in both scenarios of study

Table 2. GAPatrol's best sets of routes for both scenarios, and the types of targets ranked according to the frequency of visitation by the routes—the higher the frequency of a type, the higher the chance that its associated points are hotspots. Targets with higher probabilities to be hotspots are highlighted.

	Team1	Team2	Team3	Team4	Team5	Team6	Target Type(%)		#Crimes
Scenario1	**34**	**36**	19, **27**, 22, **4**, **14**	24, **14**, **2**, 39, **4**, 0, **31**, 24, 5, **2**, **28**, 26, 28	**28**	25, **2**, 35, 12, **27**, 1, 3, 38, **36**, **31**, 17	Drugstore	22.6	135
							Gas Station	22.6	
							Square	19.4	
							Lottery	16.1	
							Banks	12.9	
							Mall	6.4	
Scenario 2	35, **28**, 8, 31	2, **36**	5, 15, 3, **25**, 19, 14, **25**, **12**, 22, 8, **25**	**28**, 19, 7, **35**, **25**	**34**	**25**, **31**, 10, 27, **31**, 17, **12**, 21, 14	Gas Station	22.3	445
							Square	22.3	
							Drugstore	18.2	
							Lottery	18.2	
							Banks	15.0	
							Mall	0	

Table 2 brings the configuration of the best sets of routes achieved for both scenarios, indicating the types of targets they concentrate on mostly. It was easy to notice that GAPatrol could identify well, in both scenarios, the targets that are best candidates for being considered as hotspots: either GAPatrol has allocated a patrol team permanently at those points or they appear twice or more times in any route of the set. Moreover, as in both scenarios fifty percent of the patrolled targets are drugstores, squares or lotteries, it is easy to perceive that GAPatrol could somehow "learn" the behavior of the non-expert criminals by allocating more police resources for monitoring those types of places and then not allowing that the criminals become experts.

Finally, by analyzing the behavior of the best individuals of each generation of all GAPatrol executions, we could notice that this sort of hotspot elicitation was indeed very important for giving rise to effective sets of patrol routes at the end of the evolutionary process. Indeed, in the first generations, most of the hotspots were not yet localized by most of the competing sets of routes (GA individuals), which, in turn, tended to be rich in length (i.e. trying to encompass as much points as possible and not focusing on those that were indeed most important). Fig. 2 provides a pictorial illustration of one execution of GAPatrol, ratifying our arguments.

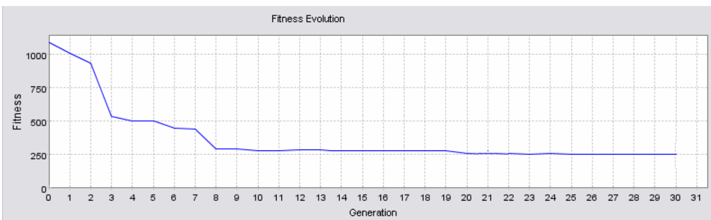

Fig. 2. GAPatrol evolutionary process: decreasing in fitness due to hotspots discovery

As future work, we plan to provide a more thorough account on the properties and characteristics underlying the best sets of routes achieved with GAPatrol. A spatial analysis of the routes is also in course, and soon the criminals shall be endowed with capabilities to learn how to better spot their points of attack.

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