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A bio-inspired crime simulation model

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ABSTRACT

In this paper we describe a multiagent crime simulation model that resorts to concepts of self-organizing bio-inspired systems, in particular, of the Ant Colony Optimization algorithm. As the matching between simulated and real crime data distributions depends upon the tuning of some control parameters of the simulation model (in particular, of the initial places where criminals start out), we have modeled the calibration of the simulation as an optimization problem. The solution for the allocation of criminals into gateways is also undertaken by a bio-inspired method, namely, a customized Genetic Algorithm. We show that this approach allows for the automatic discovery of gateway configurations that, when employed in the simulation, produce crime distributions that are statistically close to those observed in real data.

1. Introduction

Recently, an extensive analysis conducted over real crime data related to a large Brazilian metropolis [11] demonstrated that the spatial distribution of crimes such as robberies, thefts, and burglaries follows a power law, more specifically, a Zipfian distribution [40]. This means that the frequency of crime occurrences related to a specific geographic area, when considered per type of crime, tends to scale according to a power-law distribution, yielding the formation of hot spots [34]. In the same work [11], an analysis over the temporal aspect reveals that these crime events follow an exponential distribution per period of analysis.

Although knowing the crime distribution profile for a given moment may be necessary to better conduct some of the police decision-making activities, it is not enough to help one gain further insights into crime in its totality. This is because crime is a dynamic phenomenon, and the decision of protecting a frequently-attacked target at a given point in time eventually leads to the exposure of other potential targets in the future, due to a range of restrictions in terms of resources availability (e.g., human resources).

In this sense, we advocate that a better understanding of the trends of criminal activities and the types of reactions criminals might potentially undertake is a crucial task to be pursued. In this context, the goal of the research we have been conducting in the last years [18,19,31] is to produce a crime simulation system that reproduces crime phenomena as realistically as possible. Our ultimate goal is to uncover strategies for police patrolling (more precisely, police patrol routes) that could cope well with the dynamics of crime when criminal agents are capable of learning "on the fly."

In this article, we provide a major step toward the aforementioned goal by introducing a dynamic model of crime against property[1] that shows experimentally how this type of crime evolves. The main challenge behind this effort lies in the definition of a simulation model that could generate crime episodes according to a spatial Zipfian distribution and, at the same time, be in agreement with real data. For such a purpose, we have designed a multiagent criminal model that mimics real-life criminal behavior in consonance with some sociological studies [1,36], paying special attention to the following facts: *(i)* the environment where the agents live is a digitalized map representing the real-life area; *(ii)* criminals improve their performance over time by creating preferences according to their experience in crime; and *(iii)* social communication among criminals must also be properly modeled, because criminal behavior depends not only on individual incentives but also on the behavior of the perpetrators' peers and neighbors.

One distinctive aspect of the conceived criminal model is that it resorts to concepts related to self-organizing bio-inspired systems, in particular the Ant Colony Optimization (ACO) algorithm [7,15]. The rationale behind this choice is twofold. Through an ant-based

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[1] Crime against property includes burglaries, robberies, etc. as long as the main target is an establishment. Hence, situations like a *person being mugged on the street* are not included in this study.

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perspective, we can model criminals as agents that account for both the individual and social aspects we intend to consider in our crime simulation model. They are endowed with the capability to pursue self-organized behavior by considering their individual (local) activities as well as the influence of other criminals in the community they live in. At the same time, as we have identified experimentally in [18], ant-based multiagent systems are capable of reproducing spatial behavior of a power-law nature. Basically, we have shown that two features of the model lead to this important result: the possibility of social communication between criminals, and the fact that they follow a kind of preferential attachment mechanism (popularly called the *rich get richer* phenomenon) [5,25]. In the context of crime, the preferential attachment mechanism reflects the criminal preference to commit crimes in places where they feel comfortable because of their past experience and learning.

Even considering these interesting capabilities of the model, we have to point out that the matching between simulated and real crime data distributions depends very much upon the tuning of some control parameters of the simulation model; in particular, the initial places where criminals start out in the simulation process (henceforth called gateways). As this particular tuning is not trivial per se, we have decided to model it as an optimization problem. Therefore, in this paper we describe a solution for the allocation of criminals into gateways via another bio-inspired technique, namely, a customized Genetic Algorithm (GA) [17]. We show that this approach allows for the automatic discovery of gateway configurations that, when employed in the simulation, produce crime distributions that are statistically close to those observed in real data. The experiments reported here compare the matching between the spatial distribution of crimes generated from our simulator and the actual crime distribution data recorded for a region of Fortaleza, a large Brazilian urban metropolis.

The remainder of the paper is structured as follows. First, we describe related work with the theoretical basis upon which we have constructed and tuned our crime simulation model. Then, we focus on the characterization of the elements behind this model, paying special attention to the description of the criminal learning behavior and to the GA-based solution for the criminal–gateway allocation problem. The experimental results come next, evidencing that the whole bio-inspired approach is indeed capable of generating adequate criminal–gateway configurations and simulated crime distributions that are closely related to those observed in real data. We conclude by describing the relevance of these findings and providing directions for future work.

2. Multiagent simulation, ant colony optimization, and genetic algorithms

Multiagent Systems (MAS) [37] involve the study of the behavior of autonomous and organized groups of agents with the purpose of providing distributed, emergent solutions to complex problems that could not be achieved by each individual agent alone. On the other hand, the deployment of simulations for the purpose of gaining insights along a given decision-making process can be a very effective approach one could resort to, as computer simulations usually allow the focused analysis of important issues by investigating their influences, either separately or conjointly.

Recently, multiagent systems have been successfully adopted in conjunction with simulation models, as the inherent characteristics of the former (e.g., agent autonomy, reactivity, and pro-activity) facilitate the construction and simulation of more realistic and dynamic models, thus contrasting directly with conventional computer simulation approaches. The outcome is generally referred to as Multiagent-based Simulation (MABS) systems, which—according to [20]—are especially appropriate when one has to deal with interdisciplinary problem domains, such as the public-safety domain investigated here. In particular, we advocate that the multiagent approach (bottom-up in nature) is appropriate for the study of social and urban problems, since social/urban environments are dynamic, non-linear, and composed of a great number of variables and entities. As pointed out by [16], some of the main goals behind the construction of MABS systems are the following:

- To test hypotheses related to the emergence of macro-level behavior from interactions occurring at micro levels;
- To build theories that can contribute to a better understanding of sociological, psychological, and ethological phenomena; and
- To integrate partial theories coming from different disciplines (e.g., sociology, cognitive psychology, and etiology) into a common theoretical framework.

The study of agent self-organization, and related concepts such as emergence, is based on the idea that societies of agents demonstrate intelligent behavior at the collective level out of simple rules pertaining to the individual level. What is interesting behind this paradigm is that the individual rules, when considered alone, cannot explain the behavior that emerges at the collective level. Within this context, Swarm Intelligence (SI) [7] has come forth as the discipline devoted to the study of biological systems characterized by *(i)* strictly local communication; *(ii)* the formation of emergent spatial–temporal structures; and *(iii)* stochastic decisions made by the agents based solely on the local information available. One of the most well-known branches of SI deals specifically with the study of novel optimization algorithms inspired by the social behavior exhibited by some species of ants. Arguably, the main product in this line of research is the Ant Colony Optimization (ACO) algorithm [14,15], a population-based metaheuristic that has shown promising results while tackling combinatorial optimization problems that can be represented as graphs, mainly those with dynamic settings [23].

In a nutshell, ACO works as follows. Agents (ants) are endowed with the capability to explore the discrete space of solutions related to a given problem. In doing so, they leave feedback information (normally in the form of pheromone marks) on the space itself, signaling about visited locations (i.e. building blocks) associated with satisfactory solutions. On the other hand, the path each individual ant takes is directly influenced by the pheromone marks left by their peers in the environment; so, the larger the amount of pheromone in a given location, the more attractive that location becomes for being visited by the whole population of ants. By this means, even more satisfactory solutions are able to emerge by putting together those building blocks with higher levels of pheromone. In order to avoid early convergence to local optima solutions, the approach assumes that the pheromone marks are volatile; that is, the pheromone information is short-lived and, without reinforcement activity, the “hints” left in that position start to fade with time. Although it had never been explored for the purposes of modeling criminal behavior, ACO—due to its interesting properties—seemed to us to be an ideal fit to our purposes.

Like ACO, Genetic Algorithms (GA) comprehend a prominent bio-inspired population-based metaheuristic, which, in turn, is based on the mechanics of natural selection and genetics [17]. According to the GA framework, candidate solutions (referred to as chromosomes or individuals) to a given continuous/discrete optimization problem play the role of individuals in a population, while the cost (fitness) function determines the environment within which the solutions “live.” Here, optimal solutions emerge through the evolution of the population, which takes place after the repeated application of some operators mimicking well-known natural phenomena: selection for reproduction, recombination, mutation, and selection for replacement. In reproduction, parents for the next generation are selected with a bias towards higher fitness. Parents then reproduce, and offspring (new candidate solutions) is generated through recombination and mutation. Recombination acts on the two selected parents