A Crime Simulation Model Based on Social Networks and Swarm Intelligence

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ABSTRACT
Experience in the domain of criminology has shown that spatial data distribution of crime in urban centers follows a Zipf law in which few places concentrate most of the crimes while several other places have few crimes. In order to reproduce and better understand the nuances of such a crime distribution profile, we introduce in this paper a novel multi-agent-based crime simulation model that is directly inspired by the swarm intelligence paradigm. In this model, criminals are regarded as distributed entities endowed with the capability to pursue self-organizing behavior by considering their individual (local) activities as well as the influence of other criminals. Through controlled experiments with the simulation model, we could indeed observe that self-organization phenomena (i.e., criminal behavior toward crime) emerge as the result of both individual and social learning factors. At the same time, our experiments reveal that the spatial distribution of crime achieved by experimenting with the simulation model closely follows the real crime data distribution as expected.

Categories and Subject Descriptors
I.2.11 [Distributed Artificial Intelligence]: Multiagent systems

Keywords
Multiagent Simulation, Swarm Intelligence, Social Networks, Application for Law Enforcement.

1. INTRODUCTION
Most of the tools aimed at helping police experts to define their strategies of preventive policing consider the fundamental hypothesis that, by knowing where the occurrences of crime are currently happening, it is possible to make a more optimized distribution of the police resources to control (or, ideally, to decrease) the overall crime rate. These works assume the fact that crime is not spread evenly across urban landscapes; rather, it appears in relatively few places and is scarce, sometimes totally absent, in others. Recently, an extensive analysis conducted over real crime data related to a large metropolis [2] has demonstrated that the spatial distribution of crime follows a Zipf law. However, knowledge of crime distribution for a given moment is neither enough to understand crime in its totality nor to subsidize preventive police strategies. This is because crime is dynamic, and the decision of protecting a frequently attacked target will eventually lead to the exposure of other potential targets. In that sense, evaluating the trends of crime activities as well as the potential reactions of criminals when facing a certain preventive strategy is more productive for planning alternative strategies.

Simulation systems come to be a useful tool for supporting decision making in the preventive police context because they allow the police experts to experiment with the model towards the identification of hot spots (frequently attacked targets) as well as for learning about the evolution of crime at a certain scenario. This article gives an overview of a dynamic crime model that evidences experimentally how crime evolves in time after a certain preventive strategy is attempted. The task of the crime simulation model is basically to generate crimes with a spatial distribution that complies with the Zipf law. For such a purpose, we have also designed a multi-agent-based criminal model that mimics the real life where criminals improve their performance by creating preferences through experience. This criminal model resorts to concepts related both to social network analysis and self-organizing systems inspired by swarm intelligence [1]. By this means, criminals are regarded as agents endowed with the capability to achieve self-organized behavior by considering their individual (local) activities as well as the influence of other criminals in the community they live in. Through controlled experiments with the simulation model, we could indeed observe that criminal behavior toward crime is an emergent property resultant of the agent’s local interactions. At the same time, our experiments reveal that the spatial distribution of crime achieved by experimenting with the simulation model closely follows the actual crime data distribution.

2. SIMULATING CRIME AND POLICE PATROL
Basically, the simulation model has guardians (the police), targets and criminals. There is a set of police teams available, each one associated with a monitoring 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 their speeds 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 – different teams may be associated with different-sized routes which, in turn, can overlap and/or share common points of surveillance. The special locations to be patrolled are referred to as targets, which can be differentiated...
with respect to the type of establishment they represent (such as drugstores, banks, gas stations, lottery houses, squares, and malls). Only fixed targets are modelled since we are initially concentrating on crimes against the property. Targets have a state of vulnerability that can be either active or inactive. A vulnerable target means that it is perceivable to a criminal. Otherwise it would not take part in the set of choices of the criminal. Each target has a probability of being vulnerable which follows the real data temporal distribution of crimes for that target type. In doing so, we are modeling a control parameter that allows reproducing the pace of crimes per type as it happens in a real life. There is a set of criminals representing the agents that frequently try to commit the crimes. The absence of guardians is an important aspect to the crime occurrence although a non-exclusive one. 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. As the ultimate scope of our work is the preventive policing, we assume that the number of criminals is always constant during a simulation. Target selection is probabilistic based on the target’s distance and on the criminal experience. Having probabilistically selected the next type of target, the time spent 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 criminals, is taken as reference for the next simulation cycles (ticks), so that the criminals are allowed to move only during this time period. Remember that only vulnerable targets are considered in the target selection process. Finally, the decision to whether or not 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 committed and another target will be selected.

3. DISCUSSION

In order to evaluate the performance of our approach, several simulation experiments were carried out having as basis a scenario defined over an urban environment that mimics a well-known neighborhood of Fortaleza, a 2.5-million inhabitant metropolis in Brazil. In such a study, the multi-agent simulation parameters were set as follows. We modeled all the 41 fixed targets of the neighborhood such as drugstores, gas stations, lottery houses, banks, squares and malls in a 64x64 grid. The location of the targets represents an approximation of their distribution across the urban space. Each cell represents a block of 100 meters. The temporal distribution of crime follows an exponential distribution as identified by Cansado [2] in her analysis of real crime data. Thus the probability of a target being vulnerable follows an exponential distribution and consequently drives the crime occurrence of crime at that temporal pace. Six police teams were allotted to patrol the area. This number is what is used on average by the city police for the surveillance of the area. As we cannot affirm that regardless of a particular preventive police the Zipf law is always verified, we decide to use one of the routes that have typically been used by the police for that region. The number of criminals was initially 16 because the number of crimes with that quantity of criminals is close to what was verified in real data. In order to evaluate the impact of social learning on crime distribution, we ran simulations with different network topologies, namely a small-world, a scale-free, and a fully-connected network. Simulations with no communication between the criminals were also performed. The results of these experiments have demonstrated that our simulator can effectively model the behavior yielding a spatial distribution of crime according to a Zipf’s law (the expected). These results also indicate that the Zipf factor is correlated with the social factor. The simulation scenarios with social communication show high regression values ($\approx 0.85$) indicating that a Zipf Law is present. The regression factor is sensibly reduced whenever there is no criminal communication. By varying the topology of the social network, we could analyze how sensible the model is to a particular topology. The scale free and the small world networks have similar results. Even though a fully connected network is not feasible in real life, this would represent an ideal situation where every criminal communicates to every other. Thus the results obtained from this configuration were useful for measuring how distant the other configurations are to such an ideal situation. Simulations with small world and scale free configurations have shown results close to those obtained when the simulation was done with a fully connected network. This indicates what has already been observed by sociological findings [3] i.e., that small-world and scale-free network settings seem to be very efficient topologies. This is maybe because small degrees of separation between nodes allow fast rates of message flow as well as high degrees of interconnectivity between criminals. These results are the basis for our future investigations, which are intended to cope with some questions related to those treated in this paper: Can the Zipf distribution law persist through time even after a series of preventive strategies takes place? If not, how long does it take for one to notice the reestablishment of the Zipf distribution law? Is it somehow possible to avoid such reestablishment?

REFERENCES

