Using Self-organization in an Agent Framework to Model Criminal Activity in Response to Police Patrol Routes

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Abstract

The organizational structure of the police is characterized by the existence of a centralized command with the task of distributing and redistributing the police force in a region according to an analysis of crime and the factors that lead to it. On the other hand, criminals are characterized as a decentralized system in which individual agents have autonomy and act primarily based on accumulated experience they gain from their life in crime. Simulation of different strategies of physical reorganization is a first step to better understand the influence that specific police patrol routes have on the reduction of crime rates and how such decentralization can be efficiently combated. In this article we describe a tool for assisting the investigation of different strategies of agent physical reorganizations where criminal agents demonstrate emergent characteristics. We believe our simulation tool is an effective way to train the police in the effectiveness of their patrolling.

Introduction

Multi-Agents Systems (MAS) are extensively used as a tool for simulation of dynamic systems. The ability to experiment with a concept before implementing it allow us to test new ideas before using them in practice. Typically, MAS-based simulations require agent reorganizations that are carried out by external intervention of a programmer; however, for a MAS to be truly autonomous, mechanisms for dynamic agent reorganization must be in place. Dynamic adaptation refers to the modification of the structure and behavior of a MAS (i.e. adding, removing or substituting components) while the system is running (Valetto, Kaiser, & Kc 2001). Most existing approaches to reorganization are quite deterministic and consider only behavioral aspects affecting the agents (Carley & Gasser 1999; Hannebauer 2002). Recently Dignum *et al.* proposed to also consider situations in which the social structure of the agent society changes overtime (Dignum, Dignum, & Sonenberg 2004). One strategy for including adaptability in a MAS that have received some attention recently is self-organization, in particular the use of self-organized strategies inspired from biological systems (Camazine *et al.* 2003).

Geosimulation is an urban phenomena model that uses the multi-agent methodology to simulate discrete, dynamic, and event-oriented systems (Benenson & Torrens 2004). Our focus in this paper is to use self-organization, specially strategies inspired from Swarm Intelligence (Bonabeau, Dorigo, & Theraulaz 1999; Kennedy & Eberhart 2001), and demonstrate that their effect to geosimulators. In particular, we extend a simulator called ExpertCop (Furtado & Vasconcelos 2005) to have agents making decisions based primarily on local information. Our extension adds learning to the agents – criminal agents are shown to learn best locations to commit criminal activities in response to police patrolling. We also believe the same rules can be applied to police officer agents; they can be made more autonomous thus able to better protect the regions (routes) they have been assigned.

One of the crucial questions regarding crime and violence control in urban centers is how to gauge the actual impact of certain police management strategies on the behavior of criminals. This is indeed a question difficult to be answered as it seems that the effectiveness of a certain public-safety policy on a given metropolitan region depends upon an array factors including the levels of concentration of richness, the physical organization of the urban center, and the level of organization and *intelligence* of criminals. In such context, it is quite consensual that police patrolling can be considered as one of the best well-known means for implementing *preventive* strategies towards the fight against property crimes (i.e. theft, robbery, etc.).

In this article we describe a tool for assisting the investigation of different strategies of physical reorganizations. We concentrate our description on strategies that demonstrate some level of self-organization on the modeling of criminal activities and compare them with other (perhaps more naïve) modeling approaches. An agent society that simulates criminal and police behavior in a geographical region is used. In this society, artificial agents representing the police are responsible for avoiding crimes. Other agents represent the criminals in the an urban environment and are programmed to make stochastic decisions about the points to attack based on the points proximity as well as their level

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of experience about the specific points. Although the simulator can also consider other factors in the attractiveness of the points, such as the perceived amount of money (payoff) of the point, these are not considered here as they make it complex to analyze the effect of the self-organization that we want to show.

Related Works

Until recently, only a few studies had been conducted on the theme of MAS systems for studying police patrolling strategies, despite the huge benefits it can potentially bring to society as a whole. One justification of such a fact is that existing approaches to deal with some related problems, such as the traveling salesman problem (TSP), cannot be directly applied, or even adapted, to cope with the intricacies of the patrolling task. One prominent research work in such context was recently developed by (Almeida *et al.* 2004) having as basic motivation to provide answers to the following questions: What kind of MAS architecture should be selected by the designer for tackling a given patrolling task? What are the means to properly evaluate an implementation of a MAS dedicated to patrolling? To what extent parameters like size and connectivity influence the overall MAS performance? In such regard, different MAS architectures have been conceived and evaluated experimentally by some authors making it possible to elicit some preliminary guidelines for the suitable design of a MAS for patrolling. The devised methodology involves both the identification of some evaluation criteria and the definition of some dimensions of characterization of the MAS architectures.

Following another direction, (Winoto 2002) has made use of the multi-agent paradigm for representing and characterizing some important crime features. In this work, an economic perspective about crime is elaborated and the notion of impunity, which seems to be an essential factor to the increase/decrease of crime rates, is analyzed from the viewpoint of crime repression. The preventive aspect, however, is somewhat neglected by the author.

In our earlier work, we have modeled the typical profiles of criminals and police officers in terms of artificial agents in order to develop an intelligent tutorial system (Furtado & Vasconcelos 2005). The ExpertCop system consists of a full-fledged geosimulation environment focused on criminality analysis, which was conceived to support police managers in learning, through an interactivity basis of how to properly allocate the human resources currently available in a given geographical map.

Despite their innovative ideas, all of the above-mentioned approaches do not systematically investigate one important issue underlying the multi-agent patrolling task: *What is the effect of patrolling to criminal activities given that criminal agents are able to learn from their experiences?* Also, *can patrolling effectively stop crime under the assumptions of learning by criminals?* ExpertCop has the capability of dealing with criminal profiles such as the differentiation between bank robbers and pick-pocketers. However, we disregard these differences in this study to due the of having an analysis solely on learning.

Self-Organization and Swarm Intelligence

Self-organization is one of those concepts that appear in many recent articles. Yet, we defend that self-organization is not just a buzzword but it is actually responsible for a revival within intelligent systems. Societies of agents demonstrate intelligent behavior (as a collective) out of simple rules at the individual level. Moreover, these rules often do not explain the behavior that is attained at the collective level.

Most real-world self-organized strategies are inspired by biological systems (Mamei *et al.* 2006) but self-organization can be observed in many other areas such as physics, chemistry, and meteorology. What they all have in common is that the behavior of the collective seems to surpass that of the added individuals – as it is normally said, the whole is more than the sum of its parts.

Within self-organization, we can find specific areas such as swarm intelligence, where inspiration comes primarily from biological insect systems such as ants and bees. Swarm intelligence is characterized by *(i)* communication being strictly local; *(ii)* the formation of emergent spatial-temporal structures; and *(iii)* decisions taken by agents being stochastic and based solely on the local information available.

Self-organization, and in particular swarm intelligence, have been sucessfully used in multi-agent systems, such as SwarmLinda (Menezes & Tolksdorf 2003) and TOTA (Mamei, Zambonelli, & Leonardi 2003), demonstrating its potential in improving robustness, adaptiveness, and availability of applications.

Here, we use concepts derived from swarm intelligence to provide autonomy and learning capabilities to agents representing criminals in response to police activity (patrol routes). Our idea is to program the criminal agents to make decisions based on their information and show that such decisions can lead to the emergence of a global behavior where agents tend to avoid well patrolled areas – concurring with what happens in real urban environments.

The Public Safety Domain and the Police Allocation Task

The allocation of police officers in urban areas in order to perform preventive policing is one of the most important tactical management activities in criminality control. What it is intended from tactical managers is that they periodically analyze the disposition of crime in a region and perform the (re)allocation of the police force based on such analysis.

An underlying hypothesis of such allocation work is that, by knowing where the crime is taking place and its associated reasons, it is possible to make a better distribution of human resources and, consequently, decrease the overall crime rate. However, the high volumes of information that police departments have to analyze is one of the main difficulties in providing the society with effective solutions – humans in general have difficulty understanding complex relationships and causality of events.

In addition to the above, real-life experiments in this domain are hard be performed without risks such as the loss of human lives. Simulation systems come to be a prominent tool for supporting decision support . Following this point of view, in this work, we concentrate on the description of one such simulation-based tool that have been extended to add more autonomy to criminals thus allowing us to understand better the effectiveness of police patrolling.

The conceptual basis for preventive approaches and the development of some proactive policing strategies can be found in the work of Cohen and Felson (Cohen & Felson 1979), which attempts to explain the evolution of crime rates not only through the characteristics (psychological profiles) of the offenders, but also through the circumstances in which crimes occur. Basically, they point out that, in order for a criminal act takes place, three elements must coexist: *(i)* a motivated offender; *(ii)* a suitable target – either an object or person that can be attacked; *(iii)* and the absence of capable guardians, in charge of the preventive actions.

The Agent Society

We have three types of agents forming an agent society:

Notable points: They are the commercial or entertainment establishments in the area such as: drugstores, banks, gas stations, lottery houses, squares, and shopping centers. The system is able to give different importance levels to these points but to understand the effect of self-organization on criminals modeling, we have disregarded these preference in this paper.

Police: Their function is to avoid the occurrence of crimes. Each police team should have at least one route where they will be accomplishing the preventive policing of the area that makes the route. It is assumed that police officers are able to prevent crime in a surrounding area – agents have a visibility radius.

Criminals: They are the ones that execute the crimes. These agents tend to be more attracted to points closer to them. Additionally, they learn from their criminal activities in each individual point. That is, the more successful a criminal agent is in a notable point, the more likely the agent is to commit a crime there regardless of its distance.

Criminal Agent Behavior

The modeling of criminal behavior is one of the most demanding in such simulation systems given the decentralization and autonomy of these agents. As mentioned before, the allocation of the police is normally part of a somewhat centralized process in which commanders decide the routes based on the information they have at hand.

In our model, each criminal has three actions: commit a crime, not commit a crime, and move to a certain location. In order to reach a decision about the crime, they use the experience of their life of crime; in fact, they use their experience with each notable point almost independently – previous successful attempts in a notable point positively affects their "attractiveness" to that point. Second, criminals observe their proximity to the notable points – the closer the point the more likely it is that they will commit the crime at that location.

After their objective is defined, the criminals ask the environment for a route to the selected notable point. The time spent to reach a goal is calculated based on the distance to the target and on the speed of the criminal, which, in our studies, is constant and the same for all criminals. Upon arriving at a destination the decision to commit or not commit a crime is taken by the agent. This reflects the behavior in which a criminal may abandon the criminal action due to unforeseen circumstances (eg. did not like the escape route available, there were too many people around the notable point, etc.).

Each criminal has a probability of deciding to commit a crime that is based on their experience with a point and the distance to the same point. The equation below is quite common in swarm intelligent systems having foraging as their main strategy (Bonabeau, Dorigo, & Theraulaz 1999). In our case, we can say that the probability, p_{cn}, of a criminal, c, to commit a crime at notable point n, is given by:

$$p_{cn} = \frac{[\tau_{cn}]^{\alpha} \cdot [\varphi_{cn}]^{\beta}}{\sum_{\forall p \in N} [\tau_{cp}]^{\alpha} \cdot [\varphi_{cp}]^{\beta}} \qquad (1)$$

where τ_{cn} represents the learned experience of a criminal c with relation to notable point n; φ_{cn} is the inverse of the distance between the location of criminal c and the notable point n; and N is the set of all notable points the criminal c is considering in their decision to where commit the crime. The equation above is applied to all points and the decision is made with regards to which point to attempt the crime. Once the point is chosen the crime may still not take place because it was avoided (by the police) or the criminal just decided not to attempt the crime (as mentioned earlier). This yields three crime counters in the system for each point p: CO_p (counter of crimes that occurred), CA_p (counter of crimes that were avoided by the police), and CT_p (counter of the total number of crimes). One should note that $CO_p + CA_p$ is not necessarily equal to CT_p because CT_p also includes all the crimes in which the criminal agent abandoned the idea of committing the crime.

From the Equation 1, we have τ as a learned factor for the criminal and φ as a static information related to the environment. For every criminal, c, and notable point, n, the learned factor, τ_{cn}, is calculated as

$$\tau_{cn} \leftarrow \rho \cdot \tau_{cn} + (1 - \rho) \cdot \Delta\tau_{cn} \qquad (2)$$

and

$$\Delta\tau_{cn} = \frac{CO_p}{CT_p} \qquad (3)$$

where the $\Delta\tau_{cn}$ represents the experience of the criminal in a day's activity. The ratio provides the rate of success of a criminal at that notable point p.

Another important novelty in our model is the use of a negative feedback factor, ρ representing the level of forgetfulness of a criminal agent. Currently this value is the same for every agent. However we believe that Equation 2 realistically represents what takes place in criminal agents. Given that τ_{cn} represents the "level of confidence" of a criminal with a point, we write that every day (or every fixed interval of time), the agent forgets some of its previous experience and is influenced more by his *new* experience (of the last day). In essence, the $\Delta\tau_{cn}$ considers only recent values of CO_p and CT_p. Equation 2 also ensures that even if criminals had an initial streak of failures, this influence will eventually be less important in his life. In our simulations, ρ is set to 0.4 meaning that only 40% of the agents' previous experience with a particular notable point is used in the calculation of their new experience for the same point.

Later, we demonstrate that the above self-organized approach yields an emergent behavior in which criminals learn to avoid patrolling routes and concentrate their activities in areas where patrolling is low or is not present at all.

Society Organization

In the society described above, we are more interested in the behavior of criminals. By saying this we are not arguing that police patrol routes are not important. On the contrary, we believe that by using our framework to study the effect of routes to criminal activities we can effectively make decisions on what is a good configuration of patrol routes.

As mentioned before, the criminal agents in our society are decentralized and autonomous. On the other hand the organization of the police agents is eminently hierarchical. This organization follows the military structure where ranks determine the degree of authority. For the purpose of this work, we opted to represent a simple hierarchy with only one level of command. A colonel has the responsibility of defining patrol routes for a certain area of the city. Each route possesses a police team that may be composed of one or more police officers. The organizational structure is thus hierarchical and the autonomy for reorganization only exists at the central level.

We ought to point out that what our framework intends is to capture essential notions of criminal behavior in response to patrol routes configurations so that in the future this study can be useful to implement different organization schemes with some more autonomy to the police officers in each route.

Empirical evaluation of the simulation model

The main aspect that we would like to verify in our simulations is the ability of criminal agents to learn about notable points where the police patrol is not effective. This would show that indeed the Equations 1, 2, and 3, and in particular the stochastic approach taken by the criminal agents, causes them to behave as expected – flee from police activities by learning from their successes and failures.

In (Melo, Belchior, & Furtado 2005) the approach taken by the criminals is very deterministic. They basically choose a notable point category of their interest such as banks, pharmacies, etc. and after that, the simulator takes that closest notable point of the category chosen. Figure 1 shows the status of the simulation without learning (on the left) and with learning (on the right).

We have prepared a simulation system with the following characteristics: we simulate a geographical environment as a 60×60 grid with 41 notable points. There are 38 police officers patrolling routes of 1 notable point. We executed this way to observe the convergence to the other 3 points

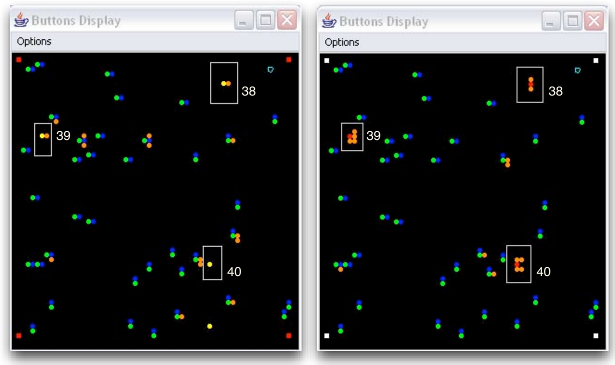

Figure 1: In the experiment on the right, the criminals tend to concentrate on the three points of this simulation that have no police patrol – the points marked by a square.

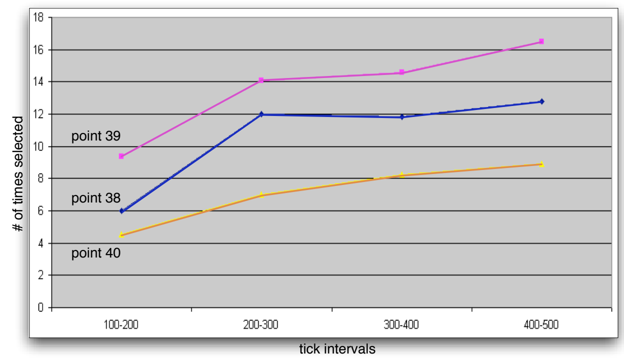

Figure 2: Figure above shows the increase in preference for notable points 38, 39, and 40

with low (no) police patrolling. There are also 15 criminals spread in the grid looking for places to commit crime.

Figure 1 shows the "snapshot view" at the end of the simulation. In this figure, the points marked by a square and labelled are known (due to the police routes assigned in the simulations) to have low patrolling. At the end of the simulation, one can clearly see that the figure on the right has three points in which the criminal activities are concentrated at (the three points that have low police patrolling) while the figure on the left has a more disperse crime activity.

From the point of view of the police force, this is a very interesting result given that it demonstrates the effectiveness of the patrolling in the other points. This means that by stopping the occurrence of crime in the patrolled points, the criminals learn (or are forced to learn) to go to other locations. In a system that includes re-organization of routes, or some level of autonomy in the patrolling, it may be possible to be even more effective (this is further discussed in the Future Work section). Again, in our simulation the police is in a certain disadvantage given the autonomy and robustness of the criminal agents who can move to anywhere they find fit.

The current simulation also allow us to study the effect of patrolling in criminal growth. In the model, one of factors for the growth of crime rate is the increase of the criminal's ability to learn what notable points provide the best cost-benefit (distance vs. notion of success rate for that point). This is represented by their experience in committing crimes *per point* that increase when they are successful in their initiatives. In other words, if there is no punishment (in this society represented by the prohibition of crime occurrence) the criminals tend to become more aware of the weak points in the city and thus commit more crimes. Simulations without reorganization of routes have shown that such factor occurs in our model.

We have identified in Figure 1, three points labeled as 38, 39, and 40. These points are known to have insufficient patrolling in the disposition of the police officer agents. Figure 2 shows the increase in the number of times these points are selected in the simulation in many intervals. The simulations are run for 500 ticks (units of time in the simulation).

Figure 2 clearly shows an increase on the preference of these points in the choice of criminal agents. This factor can be further contrasted by Figure 3. We plot the preferences per criminal agent. We selected a sample of the criminal agents and contrasted the increase of their preference. We take three points with low police patrolling and compare it with the activities on all other points.

On can clearly see that all criminal agents (identified by crm #) learn to concentrate their activities to points with low (or no) patrolling. Figure 3 shows only sample of the criminals (due to space restrictions) but the learning above happens to all agents at different scales. Since in the system the choice of notable points is stochastic, the agents continue to choose points with high patrolling – their probability decreases but never reaches zero. One should also note that in the simulation we have 41 notable points and Figure 3 is comparing 3 points with low patrolling (added together) against all other 38 points (also added together).

Discussion

One of the most important results we obtain in this work is the fact that a model to support the study of patrol routes must be consistent with some sociological theories on crime. The criminal behavior is one of the most important aspects to be modeled. Two undisputable factors are essential. The first one is that criminals prefer to commit crime in places that they are used to or are familiar with. Changing preferences leads the criminal to commit mistakes consequently reducing the criminal productivity. The distance of the target is one of the factors that define the criminal preference. Typically, the nearer the target is, the more preferable it becomes (Wright & Decker 1997). Moving the choice of target to a different location is expensive to the criminal and the outcome full of uncertainties. The second aspect, correlated with the last one, refers to the ability to learn how good (dangerous) a target is. Typically, a target is considered good depending on the individual's crime history in that target. The model we present takes both factors into account.

For studying police patrol routes, the modeling of these aspects is important because allows for the definition of routes that searches to avoid crime conversely the preferences of criminal. For instance, a good police patrol route must force criminals to often change their preferences e.g. be forced to chose distant targets. In our model the moving to a more distant target implies a reduction on the crime rate *for the entire society* – greater distances force criminals to spend more time in non-productive activities (e.g. walking to the target). Our results agrees with known theories about crime activity (Brantingham & Brantingham 1979).

Conclusion and Future Work

In this article, we described a tool to aid the configuration of reorganization strategies of police agents. In particular, the article concentrates on realistically modeling criminal activities. In order to achieve our results we used self-organization where agents learn from their individual (local) activities, and take decisions based on this learned factor and static environmental information (the distance to the notable points).

In a more general way, our model shows that self-organization is a suitable approach to the modeling of systems that aid decisions about patrolling routes. As we said before, the police force uses a hierarchical approach where commanders decide the routes based on data that is given to them. Once a number of police officers are assigned to a route, our model assumes that they stay on their route "walking" at a constant speed. Although we understand the difficulty in changing the hierarchical scheme that exist in the police force, we also believe that some level of self-organization can be added to our model bringing benefits the patrolling of each route. Police officers may be drawn to stay in points within their patrolling area based on the points' criminal history. For instance, if in a route we have two pharmacies and one bank and the bank has had a worse history of criminal activities, the police officers may decide to spend more time in that point. We are currently working on this implementation.

Another approach that we are considering for the future is to make the system more scalable so that more complex experiments can be made. This will involve a more decentralized mechanism to store information about crimes. Currently each criminal agent "stores" its own experience for each notable point. Note however that such information is also useful to police officer agents. So, we plan on having some of this experience stored at each notable point in the simulation to allow the use of the experience by the police officers. This should also improve the scalability of our simulation systems as agents become more lightweight. Furthermore, the storage of information at notable points may allow further development of the model that controls the criminal agents activities. One may envision a model where agents are not only driven by their experience with a point and the point's distance but also the experience of all other criminal agents with the same point (information that will be available at the point itself). One can see this as a sort *small-world* scenario where criminals get to know about others' activities in the points and their success rates. In fact, we are currently experimenting with a *small-world* approach

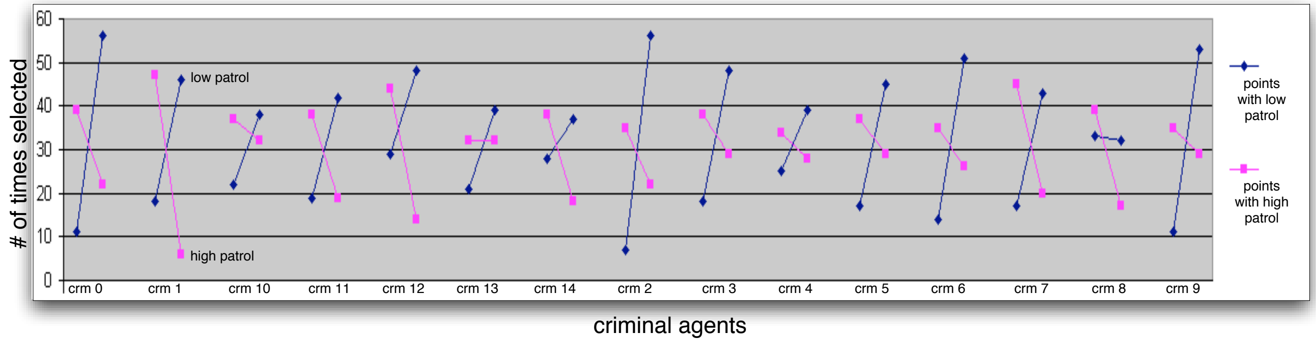

Figure 3: Criminals learn to concentrate their activities in points where their success rate is higher. Here we can see our results for a sample of points. In each case we compare 38 points (points with high patrolling) against 3 points (points with low patrolling). Most of criminal activities gets concentrated in the 3 points with low patrolling.

where criminal agents form networks and have a status (importance) in this network based on their crime history.

Last, we are also going to see the effect of other self-organization strategies in our model. One such strategy is *bacteria molding*, which advocates that the positive feedback that agents get to cluster at certain points transforms into negative feedback when the density of agents in that point becomes large. In our model, this may be used in the desirability of a point by a criminal agent. For instance, even though a notable point can be desirable due its lack of patrolling, it may be undesirable because the number of criminals already concentrated on that point is high. In other words, criminals prefer points with low patrolling but are drawn away from points where competition with other criminal agents is high.

References

Almeida, A.; Ramalho, G. L.; Santana, H. P.; Tadesco, P.; Menezes, T. R.; Corruble, V.; and Chevaleyre, Y. 2004. Recent advances on multi-agent patrolling. In *Proceedings of the 17^{th} Brazilian Symposium on Artificial Intelligence (SBIA)*, volume 3171 of *Lecture Notes on Artificial Intelligence*.

Benenson, I., and Torrens, P. M. 2004. Geosimulation: Object-based modeling of urban phenomena. *Computers, Environment and Urban Systems* 28(1,2):1–8.

Bonabeau, E.; Dorigo, M.; and Theraulaz, G. 1999. *Swarm Intelligence: From Natural to Artificial Systems*. Santa Fe Institute Studies in the Sciences of Complexity Series. Oxford Press.

Brantingham, P., and Brantingham, P. 1979. Environment, routine, and situation: Toward a pattern theory of crime. In Clark, R., and Felson, M., eds., *Routine Activity and Rational Choice: Advances in criminological Theory*, volume 5. Transaction Books. 259 – 294.

Camazine, S.; Deneubourg, J.-L.; Franks, N.; Sneyd, J.; Theraula, G.; and Bonabeau, E. 2003. *Self-Organization in Biological Systems*. Princeton Univ Press.

Carley, K., and Gasser, L. 1999. Computational organization theory. In Weiss, G., ed., *Multi-Agent Systems: A Modern Approach to Distributed Artificial Intelligence*. MIT Press. 299–330.

Cohen, L. E., and Felson, M. 1979. Social change and crime rate trends: A routine activity approach. *American Sociological Review* 44:588 – 608.

Dignum, V.; Dignum, F.; and Sonenberg, L. 2004. Towards dynamic reorganization of agent societies. In *Proceedings of the 2004 Workshop on Coordination in Emergent Agent Societies (ECAI)*, 70–78.

Furtado, V., and Vasconcelos, E. 2005. A multi-agent simulator for teaching police allocation. In *Proceedings of the 17^{th} Innovative Applications of Artificial Intelligence (IAAI 2005)*.

Hannebauer, M. 2002. *Autonomous Dynamic Reconfiguration in Multi-Agent Systems*, volume 2427 of *Lecture Notes in Artificial Intelligence*. Springer-Verlag.

Kennedy, J., and Eberhart, R. C. 2001. *Swarm Intelligence*. Morgan Kaufmann.

Mamei, M.; Menezes, R.; Tolksdorf, R.; and Zambonelli, F. 2006. Case studies for self-organization in computer science. *Journal of System Architecture*. to appear.

Mamei, M.; Zambonelli, F.; and Leonardi, L. 2003. Tuples on the air: A middleware for context-aware computing in dynamic networks. In *Proceedings of the 23rd International Conference on Distributed Computing Systems*, 342. IEEE Computer Society.

Melo, A.; Belchior, M.; and Furtado, V. 2005. Analyzing police patrol routes with the simulation of the physical reorganization of agents. In *Proceedings of AAMAS*, Multi-agent-based Simulation, 97–106.

Menezes, R., and Tolksdorf, R. 2003. A new approach to scalable linda-systems based on swarms. In *Proceedings of the ACM Symposium on Applied Computing*. Melbourne, FL, USA: ACM.

Valetto, G.; Kaiser, G. E.; and Kc, G. S. 2001. A mobile agent approach to process-based dynamic adaptation of complex software systems. In *EWSPT '01: Proceedings of the 8th European Workshop on Software Process Technology*, 102–116. London, UK: Springer-Verlag.

Winoto, P. 2002. A simulation of the market for offenses in multiagent systems: Is zero crime rates attainable? In *Multi-Agent-Based Simulation II: Third International Workshop (MABS)*, volume 2581 of *Lecture Notes in Computer Science*, 181 – 193. Bologna, Italy: Springer-Verlag.

Wright, R. T., and Decker, S. H. 1997. *Armed Robbers in Action: Stickups and Street Culture*. Northeastern University Press.