

Comparing Crime Prevention Strategies by Agent-Based Simulation

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Abstract

Within the field of Criminology, an important challenge is to investigate the spatio-temporal dynamics of crime. Typical questions in this area are how the emergence of criminal hot spots can be predicted and prevented. This paper presents an agent-based simulation approach that is able to address such questions. More specifically, the approach can be used to compare different strategies for guardian movement in terms of their effectiveness. To illustrate the approach, a number of simulation experiments have been performed, and the results are discussed.

1. Introduction

One of the main research interests within the field of Criminology is the analysis of the *displacement of crime* [5, 9, 13]. When do hot spots of high crime rates emerge? Where do they emerge? How long do they persist? And, perhaps most importantly, how can they be prevented? To answer such questions, in recent years, different computational modelling approaches are being applied, among which agent-based modelling [1, 2, 4, 12], population-based modelling [2], cellular automata [8, 11], different spatial analysis techniques [7], and evolutionary computing techniques [12].

Although they all share the aim of investigating crime displacement, the perspectives taken in the above papers differ. For example, some authors try to develop simulation models of crime displacement in existing cities, which can be directly related to real world data (e.g., [11]), whereas others deliberately abstract from empirical information (e.g., [2]). The idea behind the latter perspective is that the simulation environment is used as an analytical tool, mainly used by researchers and policy makers, to shed more light on the process under investigation, and perhaps improve existing policies (e.g., for surveillance) on the long run [6]. Also, some authors take an intermediate point of view (e.g., [1]). They initially build their

simulation model to study the phenomenon per se, but define its basic concepts in such a way that it can be directly connected to empirical information, if this becomes available.

This intermediate perspective is also taken in the research project of which the current paper is part. The main goal of the project is to develop an agent-based simulation model of crime displacement, which can be used not only to *simulate* the spatio-temporal dynamics of crime, but also to *analyse* and eventually *control* those dynamics (by means of an intelligent support agent). This second aim distinguishes it from most existing approaches, which are mainly descriptive (instead of prescriptive).

Within simulation models of crime displacement, usually three types of agents are distinguished: *criminals*, *guardians* and *passers-by*. This choice is mainly inspired by the well-known Routine Activity Theory in Criminology [5], which basically states that crime occurs when a motivated offender encounters a suitable target, while no efficient guardian is present. The idea of the simulation model proposed in the current paper is that the behavioural rules for criminals and passers-by are completely re-used from existing approaches (in particular [2]), but that the behaviour of the guardians is variable. For this, we propose different strategies, varying from reactive strategies (i.e., guardians move to a location after many crimes have been committed there) to anticipatory strategies (i.e., guardians move to a location as soon as they expect that many crimes will be committed there). The proposed simulation model can be used to investigate which strategy is most effective in a given scenario[†]. Eventually, we will develop an intelligent agent that uses such information to generate appropriate advices for the police.

The paper is organised as follows. In Section 2, the basic (domain) model about crime displacement is presented. Next, in Section 3, this domain model is

[†] In this paper we focus explicitly on crimes that are performed on the street against random passers-by, e.g. pick-pocketing.

incorporated in an analysis model that can predict the effectiveness of different crime prevention strategies based on current distributions of different types of agents. Section 4 illustrates the working of the analysis model by means of simulations, and shows how the different strategies perform in different circumstances. Section 5 concludes the paper with a summary and a discussion about future work.

2. Domain model

This section introduces the domain model for crime displacement processes, inspired by [2]. Note that agent groups are modelled in terms of their density, i.e., at a global level, not an individual level. In Section 2.1, the main aspects of the model and their relations are introduced. In Section 2.2, the formalisation of the model is provided.

2.1 Crime Displacement

The socio-temporal dynamics of crime have been a topic of criminological research for many decades. Typically, there are a number of locations in a city where most of the crimes occur, so-called *hot spots* [13]. Such locations are, for example, the railway station or a shopping mall. These locations usually have several things in common, among which the presence of many passers-by (which makes the location attractive for criminals) and the lack of adequate surveillance. However, after a while the situation often changes: the criminal activities shift to another location. This may be caused by improved surveillance systems (such as cameras) at that location, by an increased number of police officers, or because the police changed its policy.

Another reason for displacement can be that the passers-by move away because that location develops a bad reputation after a number of assaults. This *reputation* of specific locations in a city is an important factor when describing the displacement of crime [9]. For example, it may be expected that the amount of assaults that take place at a certain location affect the reputation of this location. Similarly, the reputation of a location affects the attractiveness of that location for certain types of individuals. For instance, a location that is known for its high crime rates will attract police officers, whereas most citizens will be more likely to avoid it. As a result, the amount of criminal activity at such a location will decrease, which will affect its reputation again.

To summarise, in order to describe patterns in the displacement of crime, several aspects are important. First, it is important to know the *total number* of agents

in the different groups involved, i.e., the number of *criminals*, number of *guardians*, and number of *passers-by*. Next, it is assumed that the world (or city) that is addressed can be represented in terms of a number of different *locations*. It is important to know how many agents of each type are present at each location: the *density* of criminals, guardians, and passers-by. Furthermore, to describe the movement of the different agents from one location to another, information about the *reputation* (or *attractiveness*) of the locations is needed. This attractiveness is different for each type of agent. For example, passers-by like locations where it is safe, e.g. locations where some guardians are present and no criminals. On the other hand, guardians are attracted by places where a lot of criminals are present, and criminals like locations where there are many passers-by and no guardians. Finally, to be able to represent the idea of hot spots, the *number of assaults* per location is modelled. The idea is that more assaults take place at locations where there are many criminals and passers-by, and few guardians, cf. the Routine Activity Theory by [5].

2.2 Formalisation

To formalise the concepts introduced above in italics, a number of variable names are used; see Table 1. These ideas are mostly taken over from [2].

Table 1. Variables in simulation model

Name	Explanation
c	Total number of criminals
g	Total number of guardians
p	Total number of passers by
$c(L, t)$	Density of criminals at location L at time t .
$g(L, t)$	Density of guardians at location L at time t .
$p(L, t)$	Density of passers-by at location L at time t .
$\beta(L, a, t)$	Attractiveness of location L at time t for type a agents: c (criminals), p (passers-by), or g (guardians)
$ba(L, a, t)$	Basic attractiveness of location L at time t for type a agents: c (criminals), p (passers-by), or g (guardians)
$assault_rate(L, t)$	Number of assaults taking place at location L per time unit.

The calculation of the number of agents at the various locations is done by determining the movement of agents that takes place based upon the attractiveness of the location. For instance, for the criminals the formula is specified as follows:

$$c(L, t + \Delta t) = c(L, t) + \eta \cdot (\beta(L, c, t) \cdot c - c(L, t)) \Delta t$$

This expresses that the density $c(L, t + \Delta t)$ of criminals at location L on $t + \Delta t$ is equal to the density of criminals at the location at time t plus a constant η (expressing the rate at which criminals move per time

unit) times the movement of criminals from t to $t+\Delta t$ from and to location L multiplied by Δt . Here, the movement of criminals is calculated by multiplying the relative attractiveness $\beta_{L, c, t}$ of the location (compared to the other locations) for criminals with the total number c of criminals (which is constant). From this, the density of criminals at the location at time t is subtracted, resulting in the change of the number of criminals for this location. For the passers-by, a similar formula is used:

$$p(L, t + \Delta t) = p(L, t) + \eta \cdot (\beta_{L, p, t} \cdot p - p(L, t)) \Delta t$$

However, the movement of the guardians is not necessarily modelled using this formula. Instead, the formula for guardian movement is dynamic. Here, different strategies can be filled in, see Section 3.

Next, the attractiveness of a location can be expressed based on some form of reputation of the location for the respective type of agents. Several variants of a reputation concept can be used. The only constraint is that it is assumed to be normalised such that the total over the locations equals 1. An example of a simple reputation concept is based on the densities of agents, as expressed below.

$$\begin{aligned} \beta_{L, c, t} &= p(L, t) / p && \text{for criminals} \\ \beta_{L, p, t} &= g(L, t) / g && \text{for passers-by} \end{aligned}$$

This expresses that criminals are more attracted to locations with higher densities of passers-by, whereas passers-by are attracted more to locations with higher densities of guardians. This definition of reputation is used in [2]. Although this definition is simple, which makes the model well suited for mathematical analysis, it is not very realistic. To solve this problem, in this paper, the following linear combinations of densities are used[‡]:

$$\begin{aligned} \beta_{L, c, t} &= \beta_{c1} \cdot (1 - g(L, t) / g) + \beta_{c2} \cdot p(L, t) / p + \beta_{c3} \cdot ba(L, c, t) \\ \beta_{L, p, t} &= \beta_{p1} \cdot (1 - c(L, t) / c) + \beta_{p2} \cdot g(L, t) / g + \beta_{p3} \cdot ba(L, p, t) \end{aligned}$$

This expresses that criminals are repelled by guardians, but attracted by passers-by. Similarly, passers-by are repelled by criminals, but attracted by guardians. In addition, for each type of agent some basic attractiveness can be defined. The weight factors (β_{ij} , which may also be 0) indicate the relative importance of each aspect. Again, for the guardians no formula is specified, since this depends on the guardian movement strategy that is selected.

Finally, to measure the assaults that take place per time unit, also different variants of formulae can be used (see [2]). In this paper, the following is used:

$$assault_rate(L, t) = \max(c(L, t) \cdot p(L, t) - \gamma \cdot g(L, t), 0)$$

Here, the assault rate at a location at time t is calculated as the product of the densities of criminals and passers-by, minus the product of the guardian density and a constant γ , which represents the capacity of guardians to avoid an assault. The motivation behind this is that the maximum amount of assaults that can take place at a location is $c(L, t) \cdot p(L, t)$, but that this number can be reduced by the effectiveness of the guardians (which corresponds exactly to the Routine Activity Theory). In principle, this assault rate can become less than 0 (the guardians can have a higher capacity to stop assaults than the criminals have to commit them); therefore the maximum can be taken of 0 and the outcome described above. Based on this assault rate, the total (cumulative) amount of assaults that take place at a location is calculated as:

$$total_assaults(L, t + \Delta t) = total_assaults(L, t) + assault_rate(L, t) \Delta t$$

Although the model is presented above in a purely mathematical notation, its actual implementation has been done in the agent-based modelling environment LEADSTO [3]. This environment is well suited for the current purposes, since it allows the modeller to combine qualitative, logical aspects (such as high-level agent concepts like beliefs, or decisions to follow a particular strategy) with quantitative, numerical aspects (such as real numbers and mathematical operations). Its basic building blocks are executable rules of the format $\alpha \rightarrow \beta$, which indicates that state property α leads to state property β . Here, α and β can be (conjunctions of) logical and numerical predicates. The complete LEADSTO code of the model can be found in Appendix A in [14].

3. Analysis model

In this section, the domain model presented above is extended to an analysis model. The idea is that, in addition to the rules that govern the behaviour of criminals and passers-by, the behaviour of guardians can be specified by selecting one out of multiple strategies.

Currently, most guardian investment policies of the police seem to have one main disadvantage, namely that they are reactive. That is, they only send more guardians to locations where many crimes have been committed in the past. In practice, this often means that such a decision is made too late, because the damage has already been done. Instead, we hypothesise that a more anticipatory strategy (e.g., a strategy to invest in more guardians at locations where one predicts that a hot spot *will emerge*) may be more efficient.

[‡] Note that these attractiveness formulae are not normalised yet. To ensure the values stay between 0 and 1, each attractiveness value is divided by the sum of the values over all locations. Moreover, the influence by agents from the same group is not considered.

Table 2. Guardian Movement Strategies

Strategy	Formalisation
baseline	$g(L, t + \Delta t) = g(L, t)$
reactive 1	$g(L, t + \Delta t) = g(L, t) + \eta \cdot ((c(L, t)/c) \cdot g - g(L, t)) \Delta t$
reactive 2	$g(L, t + \Delta t) = g(L, t) + \eta \cdot (aar(L, t) \cdot g - g(L, t)) \Delta t$
reactive 3	$g(L, t + \Delta t) = g(L, t) + \eta \cdot (taar(L, t) \cdot g - g(L, t)) \Delta t$
reactive 4	$g(L, t + \Delta t) = g(L, t) + \eta \cdot ((p(L, t)/p) \cdot g - g(L, t)) \Delta t$
anticipate 1	$g(L, t + \Delta t) = g(L, t) + \eta \cdot (c(L, t) + \eta_2 \cdot (\beta(L, c, t) \cdot c - c(L, t)) \cdot \Delta t) / c \cdot g - g(L, t) \Delta t$
anticipate 2	$g(L, t + \Delta t) = g(L, t) + \eta \cdot (p(L, t) + \eta_2 \cdot (\beta(L, p, t) \cdot p - p(L, t)) \cdot \Delta t) / p \cdot g - g(L, t) \Delta t$
anticipate 3	$g(L, t + \Delta t) = g(L, t) + \eta \cdot ((c(L, t) + \eta_2 \cdot (\beta(L, c, t) \cdot c - c(L, t)) \cdot \Delta t) / c + (p(L, t) + \eta_2 \cdot (\beta(L, p, t) \cdot p - p(L, t)) \cdot \Delta t) / p) / 2 \cdot g - g(L, t) \Delta t$

To investigate this, we present multiple strategies for movement of guardians (varying from reactive to anticipatory), and analyse for a number of scenarios which strategy yields the lowest assault rate.

In total, eight different strategies are explored (for their formalisation, see Table 2):

- The first strategy is a *baseline* strategy. In this case guardians do not move at all. Their density at the different locations remains stable over time.
- The second strategy we used is the *reactive 1* strategy. In this case the amount of guardians that move to a new location is proportional to the density of criminals at that location.
- The third strategy (*reactive 2*) states that the amount of guardians that move to a new location is proportional to the percentage of the assaults that have recently taken place at that location.
- The fourth strategy (*reactive 3*) states that the amount of guardians that move to a new location is proportional to the percentage of all assaults that have taken place so far at that location.
- The fifth strategy (*reactive 4*) states that the amount of guardians that move to a new location is proportional to the density of passers-by at that location.
- In the sixth strategy (*anticipate 1*), the amount of guardians that move to a new location is proportional to the density of criminals they expect that location to have in the future.
- In the seventh strategy (*anticipate 2*), the amount of guardians that move to a new location is proportional to the density of passers-by they expect that location to have in the future.
- In the eighth strategy (*anticipate 3*), the amount of guardians that move to a new location is proportional to the amount of assaults they expect that will take place at that location in the future. This predicted amount of assaults is approximated by taking the average of the expected densities of criminals and passers-by.

In the strategies *reactive 2* and *reactive 3*, the average assault rate $aar(L, t)$ and the total average assault rate $taar(L, t)$ are calculated as follows:

$$aar(L, t) = assault_rate(L, t) / \sum_{X:loc} assault_rate(X, t)$$

$$taar(L, t) = total_assaults(L, t) / \sum_{X:loc} total_assaults(X, t)$$

As can be seen from Table 2, the idea of the anticipation strategies is that the guardians use formulae that are similar to the formulae for movement of criminals and passers-by to predict how they will move in the near future. Obviously, these predictions will not be 100% correct, since they do not consider interaction between the different types of agents, but our assumption is that they may be useful means to develop an efficient strategy.

Furthermore, the parameter η , which occurs in all formulae except the *baseline* strategy, plays a similar role as in the formulae for movement of criminals and passers-by. Thus, it expresses the rate per time unit at which guardians are able to move. For a fair comparison between the different strategies, the value of this parameter is fixed among all strategies. However, different values can be taken for the parameter η_2 in the anticipation strategies. This parameter represents the speed by which the criminals and/or passers-by move in the predicted scenario (or, in other words, the distance in the future for which the prediction is made). For example, by taking a very high value for η_2 in the *anticipate 1* strategy, guardians get the tendency to move to locations that are predicted to have a high density of criminals in the very far future.

4. Simulations

To compare the guardian movement strategies, a large number of simulations have been performed, for different parameter settings. In this section, three example scenarios and their results are discussed. The scenarios are described in Section 4.1, and the simulation results are discussed in Section 4.2.

4.1 Scenarios

For the simulations described in this paper, three different scenarios were used. In each of the scenarios there are four locations (called L1, L2, L3, and L4).

In the *first scenario*, all locations start out with the same basic attractiveness for passers-by (i.e.,

$ba(L1,p,1) = ba(L2,p,1) = ba(L3,p,1) = ba(L4,p,1) = 0.25$). After a while (from time point 50), a new department store is opened at location L1. This store attracts lots of passers-by. As a result, the (relative) basic attractiveness of one of the locations increases (i.e., $ba(L1,p,50) = 0.7$, $ba(L2,p,50) = ba(L3,p,50) = ba(L4,p,50) = 0.1$).

In the *second scenario*, again all locations have the same basic attractiveness (0.25) at the start. After a while (from time point 25), a circus is coming to town, which temporarily increases the basic attractiveness of location L1 (i.e., $ba(L1,p,25) = 0.7$, $ba(L2,p,25) = ba(L3,p,25) = ba(L4,p,25) = 0.1$). Some time later (time point 50), the circus moves away to another city and the basic attractiveness of all location becomes equal again (0.25).

In the *third scenario*, initially all locations have the same basic attractiveness (0.25). Then, at location L1, where a department store is situated, a sale starts (at t.p. 20). This sale attracts lots of passers-by ($ba(L1,p,20) = 0.7$, $ba(L2,p,20) = ba(L3,p,20) = ba(L4,p,20) = 0.1$). After some time (t.p. 30) another department store in the city (at location L2) also starts a sale. At this time both department stores are attractive for passers-by ($ba(L1,p,30) = ba(L2,p,30) = 0.4$, $ba(L3,p,30) = ba(L4,p,30) = 0.1$). After some more time (t.p. 40) the first sale ends, which makes the first department store less attractive ($ba(L2,p,40) = 0.7$, $ba(L1,p,40) = ba(L3,p,40) = ba(L4,p,40) = 0.1$).

Other parameter settings were chosen as follows[§]. The total population consists of 800 criminals, 400 guardians, and 4000 passers-by. Initially, these agents are distributed equally over the four locations (i.e., each location contains 200 criminals, 100 guardians, and 1000 passers-by). The attractiveness settings for criminals are $\beta_{c1}=0.4$, $\beta_{c2}=0.6$, $\beta_{c3}=0$ (i.e., the biggest part of their behaviour is determined by the desire to assault, and a smaller part by the desire to not get caught, whereas no basic attractiveness plays a role for them). The attractiveness settings for passers-by are $\beta_{p1}=0.1$, $\beta_{p2}=0.1$, $\beta_{p3}=0.8$ (to enforce a high influence of basic attractiveness). In all strategies, the speed factors (η) are set to 0.5 for all agents. Furthermore, $\eta_2=10$ in the *anticipate 1* and the *anticipate 2* strategy, and two variants of the *anticipate 3* are shown: one with $\eta_2=10$ (called *anticipate 3a* from now on) and one with $\eta_2=30$ (called *anticipate 3b*), which turned out to improve the results for that strategy. The value of γ (the capacity of guardians to avoid an assault) is set to 1950 (since this produced

[§] All scenarios and parameter settings were chosen after a number of brainstorm sessions with experts in criminology. Although the numbers do not correspond to actual empirical data, they were selected in such a way that the resulting patterns are plausible.

most realistic patterns). Finally, $\Delta t=0.1$, and the total simulation time is 100 steps.

4.2 Simulation Results

The results of testing all strategies against the three scenarios described in Section 4.1 are shown in Table 3. As can be seen in this table, the crime rates differ significantly between the different strategies. The strategies *reactive 1* and *anticipate 1* (which react to the current or predicted amount of criminals, respectively) hardly seem to add anything compared to the *baseline* strategy. All other strategies seem to be beneficial. Overall, the *anticipate 2* strategy turns out to yield the lowest crime rates in most the scenarios. This is particularly the case in scenario 1 and 3. In both of these scenarios, a hot spot emerged for a longer period. In scenario 2 however, a case where a hot spot emerged but also disappeared after a while, *reactive 3* turned out to be the best strategy.

Table 3. Total amounts of assaults

	scenario 1	scenario 2	scenario 3
baseline	906.6	772.0	1413.7
reactive 1	884.2	715.6	1364.6
reactive 2	206.6	232.3	230.0
reactive 3	331.4	140.0	652.7
reactive 4	509.6	491.3	682.0
anticipate 1	847.9	691.3	1301.0
anticipate 2	184.4	192.3	174.6
anticipate 3a	499.7	413.2	718.8
anticipate 3b	227.6	374.3	360.8

For the given scenarios, *anticipate 2* turned out to be the best overall strategy. When using this strategy, guardians move to a location where they expect lots of passers-by to be in the future. This is an interesting finding, since guardians in current practice typically move to locations where many criminals are present, or many assaults are taking place.

To provide more details on the simulation results, the dynamics of two example simulation traces, as well as a detailed graphical representation of the numbers in Table 3, are shown, respectively, in Appendix B and C in [14].

5. Discussion

Since a number of years, computational modelling of crime displacement is a hot topic. As mentioned in the introduction, various modelling approaches have been taken, with different perspectives and goals. Due to space limitations, we will not provide a complete comparison here, but the interested reader is referred to [10] for a comprehensive overview.

The current paper extends this literature by proposing an agent-based simulation approach to compare different crime prevention strategies. The goal of the guardians involved was to distribute in such a way over the different locations that the crime rates were kept as low as possible. Various strategies were introduced, varying from reactive to anticipatory strategies, and were applied to different scenarios. The results indicate that the best results are produced by the strategy where the guardians move to new locations based on the expected amount of passers by in the near future. In addition, several other strategies produced good results as well.

Although these findings are encouraging, one should keep in mind that the results should not be over-generalized. They were achieved in simulations that made use of several specific parameters and simplifying assumptions. For example, in practice it will not always be feasible to determine exact numbers for the attractiveness of a location for certain groups, or even for the amount of assaults that take place. Nevertheless, the results of such simulations may be very useful input for policy makers, in order to elaborate their thoughts about efficient strategies (cf. [6]). In that sense, an advantage of having multiple strategies is that one can select the one that is most feasible in a particular situation.

As a first step to support such policy making, for future work it is planned to incorporate the presented simulation model within an intelligent support agent. Such an agent will use input from databases on citizen activities and crime records, in order to provide the police appropriate advice on how to handle in a given situation. When doing this, an important aspect that will have to be included in the model (and has been ignored so far) is the *costs* of a particular action. Discussions with experts in criminology have confirmed that this is a promising future direction.

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