Agent-Based Simulation of the Spatial Dynamics of Crime: On the Interplay between Criminal Hot Spots and Reputation

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ABSTRACT

An important challenge within the field of Criminology is to investigate the spatio-temporal dynamics of crime. Typical questions in this area are how the behaviour of offenders, targets, and guardians, and the emergence and displacement of criminal hot spots can be predicted. This paper presents an agent-based simulation model that can be used as an experimental tool to address such questions. The simulation model particularly focuses on the interplay between hot spots and reputation. Using the model, a number of simulation experiments have been performed, of which results have been analysed using formal techniques. The results indicate that the presented approach is able to adequately reproduce displacement patterns as described in the literature.

Categories and Subject Descriptors

I.6.3 [**Simulation and Modeling**]: *Applications*.
J.4 [**Social and Behavioral Science**]: *Sociology*.

General Terms

Experimentation, Human Factors, Verification.

Keywords

Criminal Hot Spots, Reputation, Social Simulation, Analysis.

1. INTRODUCTION

The field of Criminology, which addresses the analysis of criminal behaviour, is a multidisciplinary area with a high societal relevance; e.g., [12, 14, 16]. Although criminal behaviour is shown by a minority of the overall population, it typically comes in many types and variations. One of the main challenges within Criminology is to predict and explain in which situations which types of criminal behaviour will occur.

To address this challenge, several theories have been proposed within the criminological literature. Perhaps the most influential of these is the Routine Activity Theory by [12]. This (informal) theory identifies three parties that are relevant in the analysis of crime, i.e., *offenders*, *targets*, and *guardians*. More precisely, it states that a crime will occur when a motivated offender meets a suitable target and there is no guardian present.

Another important theory, which focuses on targets and guardians only, is the theory of Situational Crime Prevention [11]. This theory states that certain crimes can be prevented by placing guardians at appropriate locations. Such guardians may vary from police officers to alarm systems or surveillance cameras.

Theories like the Routine Activity Theory and the theory of Situational Crime Prevention have triggered a widespread attention for the interplay between the behaviour of offenders, targets, and guardians, and in particular for their spatio-temporal dynamics. For example, a relevant question is which factors influence the emergence of so-called *hot spots* - areas in which many crimes occur [24]. Based on the idea of hot spots, several related questions may be asked, among which:

- does the location of hot spots change over time?
- how can the emergence of hot spots be predicted?
- how can the emergence of hot spots be prevented?
- what is the relation between the emergence of hot spots and the geography of a city?
- what is the relation between the emergence of hot spots and the demographics of the population?

In the last decades, there has been a growing interest in the area of Agent Based Social Simulation (ABSS). In this field, which integrates approaches from agent-based computing, computer simulation, and the social sciences, researchers try to exploit agent-based simulation to gain a deeper understanding of social phenomena [15]. Since ABSS combines the advantages of the agent paradigm (e.g., autonomy of the individual agents) with those of social simulation (e.g., the possibility to perform scalable social “experiments” without much effort), it turns out to be particularly appropriate to analyse phenomena within the criminological domain. Indeed, in recent years, a number of papers have successfully tackled criminological questions using ABSS, e.g., [2, 8, 9, 17, 20, 21].

Despite the encouraging results by papers such as the ones mentioned above, agent based simulation models of crime can still be improved in several ways. A specific aspect that has only marginally been addressed by current approaches is the role of *reputation* [10]. Therefore, the current paper introduces an ABSS approach that specifically incorporates a notion of reputation of the locations involved.

The proposed approach makes use of the high-level declarative modelling language TTL [5] and its executable sublanguage LEADSTO [6]. This modelling language 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, actions, and observations) with quantitative, numerical

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aspects (such as real numbers and mathematical operations). Moreover, since the language has a formal logical semantics, simulation models created in TTL and LEADSTO can be formally analysed by means of logical analysis techniques (see, e.g., [4]).

Below, in Section 2, some background on the concepts of reputation and displacement is provided. Next, in Section 3, the modelling languages TTL and LEADSTO are introduced. Based on this modelling approach, Section 4 describes the simulation model for the behaviour of offenders, targets, and guardians in detail. In Section 5, the simulation results are presented and in Section 6 these results are analysed using formal techniques. Section 7 discusses related work, and Section 8 concludes the paper with a discussion.

2. REPUTATION AND DISPLACEMENT

According to the literature in criminology, the reputation of specific locations in a city is an important factor in the spatio-temporal dynamics of crime [18]. For example, it may be expected that the amount of assaults and the amount of arrests that take place at a certain location influence the reputation of this location. Similarly, the reputation of a location influences 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. As can be seen from this example, the change of the reputation of locations is a highly dynamic process. Moreover, this change of reputations goes hand in hand with the change of hot spots, which is typically known as the *displacement* problem [3, 13, 23].

Inspired by this displacement problem, the current paper proposes to include the notion of reputation within simulation models of crime. Whereas the notion of reputation is a well-known concept in the area of Artificial Intelligence e.g., [10], it is not addressed in much detail within the existing ABSS approaches to crime, such as [2, 8, 9, 17, 20, 21].

For this reason, the main objective of the current paper is to introduce an ABSS approach that incorporates the notion of reputation. In particular, the proposed approach aims at answering a specific question: how to better understand the interplay between criminal hot spots and reputation? The model can be used as an experimental tool to address this question (and related questions), by offering the possibility to predict displacement patterns under various environmental circumstances (often called "what if"-scenarios).

Typically, the input parameters of such a model are certain characteristics of the environment and the population. Examples of environmental characteristics are geographical aspects like the amount of locations, their connections, and the distances between them. Examples of characteristics of the population are the amount of agents and the ratio between offenders, targets, and guardians. Such information may or may not correspond to the characteristics of existing cities. A number of empirical criminological studies exist that try to capture such data in real cities, e.g., [7]. In such cases, the resulting empirical data (or an abstraction of them) may directly be used as input parameters for the simulation model. Based on this input, the output of the model shows the spatial behaviour of the different types of agents over time. Such simulation results enable the analyst to make certain predictions about the displacement of crime in a certain city, given certain circumstances.

3. MODELLING APPROACH

To model the different aspects of criminal displacement from an agent perspective, an expressive modelling language is needed. On the one hand, qualitative aspects have to be addressed, such as observations, beliefs, decisions to perform an assault or an arrest, and some aspects of the environment such as the presence of certain agents. On the other hand, quantitative aspects have to be addressed. For example, the reputation of locations can best be described by a real number, and the update of this reputation can best be described by a mathematical formula. Another requirement of the chosen modelling language is its suitability to express on the one hand the basic mechanisms of criminal displacement (for the purpose of simulation), and on the other hand more global properties of criminal displacement (for the purpose of logical analysis and verification). For example, basic mechanisms of displacement of crime involve decision functions for individual agents, whereas examples of global properties are the types of statements as put forward in the introduction, like "the location of hot spots changes over time".

The predicate-logical Temporal Trace Language (TTL) [5] fulfils all of these desiderata. It integrates qualitative, logical aspects and quantitative, numerical aspects. This integration allows the modeller to exploit both logical and numerical methods for analysis and simulation. Moreover it can be used to express dynamic properties at different levels of aggregation, which makes it well suited both for simulation and logical analysis.

The TTL language is based on the assumption that dynamics can be described as an evolution of states over time. The notion of state as used here is characterised on the basis of an ontology defining a set of physical and/or mental (state) properties that do or do not hold at a certain point in time. These properties are often called *state properties* to distinguish them from dynamic properties that relate different states over time. A specific state is characterised by dividing the set of state properties into those that hold, and those that do not hold in the state. Examples of state properties are 'agent 1 performs an assault on agent 2', or 'there are 5 criminal agents at location A'. Real value assignments to variables are also considered as possible state property descriptions.

To formalise state properties, ontologies are specified in a (many-sorted) first order logical format: an *ontology* is specified as a finite set of sorts, constants within these sorts, and relations and functions over these sorts (sometimes also called signatures). The examples mentioned above then can be formalised by n-ary predicates (or proposition symbols), such as, for example, performed(assault_at(a1,a2)) or number_of_criminals(locA, 5). Such predicates are called *state ground atoms* (or *atomic state properties*). For a given ontology Ont, the propositional language signature consisting of all ground atoms based on Ont is denoted by APROP(Ont). One step further, the *state properties* based on a certain ontology Ont are formalised by the propositions that can be made (using conjunction, negation, disjunction, implication) from the ground atoms. Thus, an example of a formalised state property is number_of_criminals(locA, 5) & number_of_criminals(locB, 3). Moreover, a *state* S is an indication of which atomic state properties are true and which are false, i.e., a mapping S: APROP(Ont) $\rightarrow$ {true, false}. The set of all possible states for ontology Ont is denoted by STATES(Ont).

To describe dynamic properties of complex processes such as the displacement of crime, explicit reference is made to *time* and to *traces*. A fixed time frame T is assumed which is linearly ordered. Depending on the application, it may be dense (e.g., the real numbers) or discrete (e.g., the set of integers or natural numbers or a finite initial segment of the natural numbers). Dynamic properties can be formulated that relate a state at one point in time to a state at another point in time. A simple example is the following (informally stated) dynamic property about the number of criminals at a certain location:

For all traces γ,
there is a time point t such that
at location A, there are at least x criminal agents.

A *trace* γ over an ontology Ont and time frame T is a mapping γ : T $\rightarrow$ STATES(Ont), i.e., a sequence of states γ_t (t $\in$ T) in STATES(Ont). The temporal trace language TTL is built on atoms referring to, e.g., traces, time and state properties. For example, 'in trace γ at time t property p holds' is formalised by state(γ, t) |= p. Here |= is a predicate symbol in the language, usually used in infix notation, which is comparable to the Holds-predicate in situation calculus. *Dynamic properties* are expressed by temporal statements built using the usual first-order logical connectives (such as $\neg$, $\wedge$, $\vee$, $\Rightarrow$) and quantification ($\forall$ and $\exists$; for example, over traces, time and state properties). For example, the informally stated dynamic property introduced above is formally expressed as follows:

$\forall\gamma$:TRACES $\exists$t:TIME $\exists$i:INTEGER
state(γ, t) |= number_of_criminals(locA, i) & i≥x

In addition, language abstractions by introducing new predicates as abbreviations for complex expressions are supported.

To be able to perform (pseudo-)experiments, only part of the expressivity of TTL is needed. To this end, the executable LEADSTO language [6] has been defined as a sublanguage of TTL, with the specific purpose to develop simulation models in a declarative manner. In LEADSTO, direct temporal dependencies between two state properties in successive states are modelled by *executable dynamic properties.* The LEADSTO format is defined as follows. Let α and β be state properties as defined above. Then, the notation $\alpha \twoheadrightarrow_{e, f, g, h} \beta$ means:

If state property α holds for a certain time interval with duration g,
then after some delay between e and f
state property β will hold for a certain time interval with duration h.

As an example, the following executable dynamic property states that "if an agent a goes to a location l during 1 time unit, then (after a delay between 0 and 0.5 time units) this agent will be at that location for 5 time units":

$\forall$a:AGENT $\forall$l:LOCATION
performed(a, go_to_location(l)) $\twoheadrightarrow_{0, 0.5, 1, 5}$ is_at_location(a, l)

Based on TTL and LEADSTO, two dedicated pieces of software have recently been developed. First, the LEADSTO Simulation Environment [6] takes a specification of executable dynamic properties as input, and uses this to generate simulation traces. Second, to automatically analyse the resulting simulation traces, the TTL Checker tool [5] has been developed. This tool takes as input a formula expressed in TTL and a set of traces, and verifies automatically whether the formula holds for the traces. In case the formula does not hold, the checker provides a counter example, i.e., a combination of variable instances for which the check fails.

For more details of the LEADSTO language and simulation environment, see [6]. For more details on TTL and the TTL Checker tool, see [5].

4. THE SIMULATION MODEL

This section describes the simulation model in detail, based on the LEADSTO language. The geographical aspects of the environment are modelled by a graph that consists of a number of locations, some of which are connected by edges. Within this environment, several agents move around and meet at the different locations. There are three types of agents: *criminals* (i.e., possible offenders), *passers-by* (i.e., possible targets), and *guardians*. The passers-by are assumed to be suitable targets, for example, because they appear rich and/or weak. However, as also the guardians are moving around, such targets may be protected, whenever at the same location a guardian is observed by the criminal (i.e., social control). Thus, a criminal agent will only perform a crime when it is at a location where it observes a passer-by and no guardians. An example of a simple geographical environment is shown in Figure 1. This picture represents a small city that only consists of three important locations (called A, B, and C), and is populated by 30 agents. The black circles denote passers-by, the grey circles denote guardians, and the white circles denote criminals. As can be seen in the figure, in this situation crimes may be performed at location B, since this location contains 1 criminal, 4 passers-by, and no guardians.

The interaction between a specific agent and the environment is modelled by (1) observation, which takes information on the environment as input for the agent (e.g., at which location it is, where suitable targets are, and whether social control is present), and (2) performing actions, which is an output of the agent affecting the state of the world (e.g., going to a different location, or committing a crime).

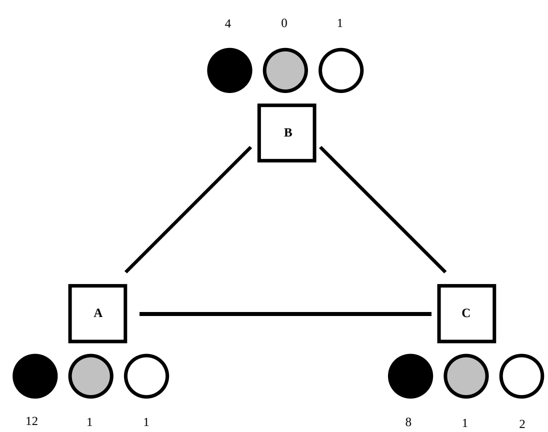

Figure 1: Example geographical environment

In order to decide to which location they will go, all agents continuously update the *attractiveness* they assign to each location, which is represented by a real number in the domain [0,1]. This attractiveness is calculated as the weighted sum of three values (also represented by real numbers), namely:

1) The individual *basic attractiveness* v the agent assigns to that location. This represents the extent to which the agent likes to go to that location, independent of its reputation. For example, some agents are more likely to go to a shopping centre, whereas others are more likely to go to a railway station.
2) The *assault reputation* n1 of the location. The higher this number, the more famous the corresponding location is for assaults taking place there.
3) The *arrest reputation* n2 of the location. The higher this number, the more famous the corresponding location is for arrests taking place there.

This calculation is represented by the following executable dynamic property (in LEADSTO format):

Decide Current Location Attractiveness
∀a:AGENT ∀l:LOCATION ∀n1,n2,v,w1:REAL ∀w2,w3:INTEGER
basic_attractiveness_of_agent_for_location(v, l, a) ∧
belief(a, assault_reputation_at_location(n1, l)) ∧
belief(a, arrest_reputation_at_location(n2, l)) ∧
has_weight_factor(a, w1, w2, w3) ↠
belief(a, current_attractiveness_of_location(l, w1*v+w2*n1+w3*n2))

As can be seen from this rule, each agent possesses three individual *weight factors* w1, w2, and w3, which indicate the relative importance they attach to each of the three components introduced above. Note that these weight factors may be positive or negative. For instance, criminals will usually have a positive weight factor for assault reputation (they will tend to go to locations where many assaults have been performed in the past, since they expect that their chances to perform a next assault are higher at those locations), and a negative weight factor for arrest reputation (they will tend to avoid locations where many arrests have been performed in the past). Similarly, passers-by will usually have a very negative weight factor for assault reputation and a negative weight factor for arrest reputation. Finally, guardians will usually have a very positive weight factor for assault reputation and a positive weight factor for arrest reputation.

Based on the calculated attractiveness of the locations, each agent determines where to go, by selecting the location with the highest attractiveness.

Moreover, as mentioned above, the criminal agents decide to perform an assault when they are at a location where they observe a passer-by and no guardians, cf. the Routine Activity Theory [12]. This is modelled by the following dynamic property:

Perform Assault
∀a1,a2:AGENT ∀l:LOCATION
observes(a1, agent_of_type_at_location(a1, criminal, l)) ∧
observes(a1, agent_of_type_at_location(a2, passer_by, l)) ∧
not guardian_at_location(l) ↠
performed(a1, assault_at(a2, l))

After having performed an assault, a criminal becomes a *known criminal* for a number of time steps. This is done to ensure that the guardians are able to recognise (and possibly arrest) a criminal that performed a crime. In the simulation experiments described in the next section, criminals stay "known" for 4 iterations, which represents a period during which they are actually being wanted by the police. After such a period, these criminals become anonymous again. However, when a guardian meets a criminal that is still wanted, (s)he will arrest that criminal. This is modelled by the following dynamic property:

Perform Arrest
∀a1,a2:AGENT ∀l:LOCATION
observes(a1, agent_of_type_at_location(a1, guardian, l)) ∧
observes(a1, agent_of_type_at_location(a2, criminal, l)) ∧
known_criminal(a2) ↠
performed(a1, arrest_at(a2, l))

Furthermore, the assault reputation of the different locations involved is increased each time that an assault is performed, cf. the following dynamic property:

Assault Reputation Increment
∀l:LOCATION ∀n:REAL
assault_at(l) ∧
belief(all_agents, assault_reputation_at_location(n, l)) ↠
belief(all_agents, assault_reputation_at_location(n+inc, l))

Here, inc is a constant that specifies the increment of reputation based on one assault. In the simulation experiments described in the next section, inc = 1. Note that this dynamic property assumes that all agents have the same knowledge about reputations. By replacing all_agents by a variable for a specific agent, variants of this rule can be created for different agents.

When no assault is performed at a location, the reputation of this location for being a hot spot slightly decreases:

Assault Reputation Decay
∀l:LOCATION ∀n:REAL
belief(all_agents, assault_reputation_at_location(n, l)) ∧
not assault_at(l) ↠
belief(all_agents, assault_reputation_at_location(n*dec, l))

Here, dec is a constant that specifies the decay of reputation when there is no assault. In the simulation experiments described in the next section, dec = 0.99.

To update the arrest reputation of locations, the same rules are used as shown above, where the word assault is replaced by arrest.

Finally, it is assumed that the (assault and arrest) reputation of all locations is known to all agents in the population (e.g., because events like assaults and arrests are publicly discussed in the media, or because they are communicated between agents). However, the approach could be made more realistic by replacing the reputation mechanism by specific trust update mechanisms for individual agents, cf. [10, 19].

The complete set of LEADSTO rules used for the simulation model (including the time parameters) is shown in Section 1 of the appendix in [25].

5. SIMULATION RESULTS

The simulation model as described in the previous section has been used to generate various simulation traces under different parameter settings. This section describes an example of a simulation trace in detail. In the next section, the global results of all simulation experiments are summarised and discussed.

The parameter settings used for the simulation described in this section are identical to the ones shown in Figure 1: the population consists of 24 passers-by, 2 guardians and 4 criminals. Initially, these agents are distributed over the locations by means of their personal preferences (i.e., the basic_attractiveness predicates). Moreover, weight factors are assigned to each agent. The details of these parameter settings can be found in Section 2 of the appendix in [25].

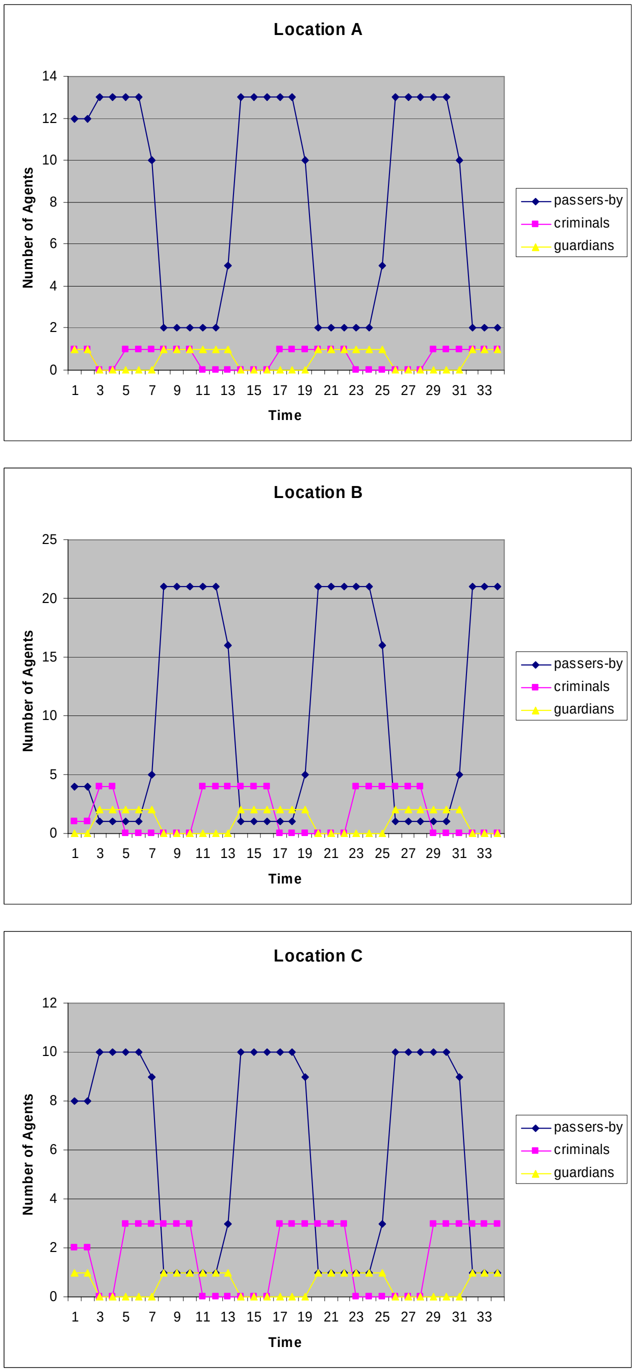

Figure 2: Displacement of the three types of criminals

Part of the simulation trace that was generated using these settings is shown in Figure 2 (A-C). Within these graphs, time is on the horizontal axis, and the number of agents at a certain location is at the vertical axis. As shown in Figure 2B (and also in Figure 1), initially there are no guardians at location B. As a result, some assaults take place at that location. This leads to a change in the assault reputation of that location, which eventually results in displacement. This can be seen at iteration 3: most of the passers-by move away from location B (although one of them still remains at that location), whereas all criminals and all guardians move towards location B. As a result of this, some arrests take place, which leads to a change in arrest reputation of location B. As a consequence, again, the criminals move (at iteration 5), this time to location A and C. Since location A and C are now populated by criminals and passers-by, but not by guardians, some assaults take place at that location, which again leads to a change in assault reputation, and in displacement of the passers-by and the guardians. This cycle repeats itself until the end of the simulation: first the passers-by move away from the criminals (and if possible, towards the guardians), then the criminals follow the passers-by (as long as they do not encounter too many guardians), and then the guardians follow the criminals.

To understand the influence of assaults on the assault reputation, see Figure 3, which depicts the dynamics of the assault reputation of location A. Note that, as opposed to Figure 2, this picture is a screenshot of the LEADSTO simulation environment[1]. As shown in Figure 3, whenever an assault is performed, the assault reputation of this location immediately increases. However, when no assaults are performed, the assault reputation gradually decreases.

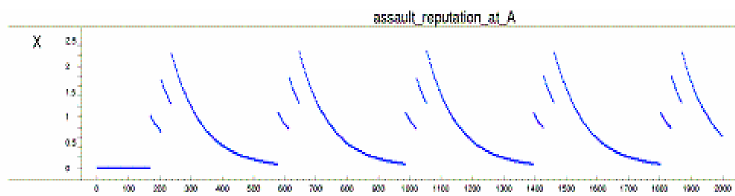

Figure 3: Assault reputation of location A

A similar trend can be observed in Figure 4, which depicts the dynamics of the arrest reputation of location A. Due to space limitations, the dynamics of the reputations of the other locations are not shown. However, these show similar behaviour as depicted in Figure 3 and 4.

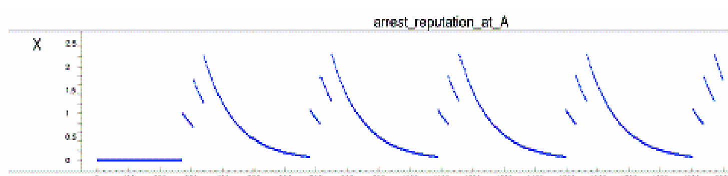

Figure 4: Arrest reputation of location A

[1] Here, time point 40 corresponds to iteration 1 in Figure 2. Time point 70 corresponds to iteration 2, time point 100 corresponds to iteration 3, and so on.

6. FORMAL ANALYSIS

All in all, a large series of simulation experiments has been performed. The detailed settings and results of three of these experiments (including the one described in Section 5.1) are shown in [25]. Among the different experiments, various parameter settings were varied, in particular the number of agents, the ratio between different types of agents, the number of locations, the basic attractiveness of locations for the agents, and the weight factors of the agents.

To analyse the resulting simulation traces in more detail, the TTL Checker tool [5] has been used. As mentioned earlier, this tool takes as input a TTL formula and a set of traces, and verifies automatically whether the formula holds for the traces. For the current domain, a number of hypotheses have been expressed as dynamic properties in TTL, which were inspired by the questions mentioned in the Introduction. For example, consider the following dynamic property (P1), which expresses that the location of hot spots keeps on changing over time:

P1 Continuation of Displacement

For each time point t (except the end of the trace[2]), if at t the largest hot spot is at location x, then there is a later time point at which the largest hot spot is at some other location y.

∀γ:TRACES ∀t:TIME ∀x:LOCATION
[is_largest_hot_spot_at(x, t, γ) & t < last_time-δ]
⇒ [∃t2:TIME ∃y:LOCATION is_largest_hot_spot_at(y, t2, γ) &
t<t2 & x≠y]

In this formula, is_largest_hot_spot_at is an abbreviation, which can be determined in multiple ways. For example, by taking the location: 1) with the highest assault reputation, 2) with the highest number of criminals, or 3) with the highest number of crimes. These different possibilities are formalised as follows:

is_largest_hot_spot_at(x,t,γ) ≡
∃r:REAL state(γ, t) |= assault_reputation(x, r) &
∀y:LOCATION ∀r2:REAL
[state(γ, t) |= assault_reputation(y, r2) ⇒ r2≤r]

is_largest_hot_spot_at(x,t,γ) ≡
∃i:INTEGER state(γ, t) |= number_of_criminals(x, i) &
∀y:LOCATION ∀i2:INTEGER
[state(γ, t) |= number_of_criminals(y, i2) ⇒ i2≤i]

is_largest_hot_spot_at(x,t,γ) ≡
∃i:INTEGER state(γ, t) |= number_of_crimes(x, i) &
∀y:LOCATION ∀i2:INTEGER
[state(γ, t) |= number_of_crimes(y, i2) ⇒ i2≤i]

In addition, a combination of the different options can be considered, for example, by calculating the weighted sum of the different numbers. Yet another variant of the dynamic property can be created, for example, by counting the number of criminals or crimes over a longer time period, instead of considering the current time point only.

Besides checking whether the location of hot spots is continuously changing, also other properties can be verified. A relevant property from the viewpoint of crime prevention is to check whether specific reoccurring patterns can be identified. For example, is it always the case that the criminals follow the movement of the passers-by, and that the guardians follow the criminals? And if not, are there specific circumstances in which this pattern does not occur? To analyse these kinds of patterns, properties like the following have been established:

P2 Criminals follow Passers-by

For each time point t (except the end of the trace), if at t most passers-by are at location x, then within ε time points most criminals will be at location x.

∀γ:TRACES ∀t:TIME ∀x:LOCATION
[most_passers_by_at(x, t, γ) & t < last_time-δ]
⇒ [∃t2:TIME most_criminals_at(x, t2, γ) & t<t2 & t2<t+ε]

Here, most_passers_by_at is defined as follows:

most_passers_by_at(x,t,γ) ≡
∃i:INTEGER state(γ, t) |= number_of_passers_by(x, i) &
∀y:LOCATION ∀i2:INTEGER
[state(γ, t) |= number_of_passers_by(y, i2) ⇒ i2≤i]

Similarly, most_criminals_at is defined by taking the location with the highest number of criminals (see the second formalisation of is_largest_hot_spot_at above). In addition to P2, a similar property has been created to check whether the guardians follow the criminals.

Finally, a number of properties have been specified to investigate the relation between the emergence of hot spots and the number of locations, and the relation between the emergence of hot spots and the ratio between the types of agents. Due to space limitations, these properties are not shown here.

To summarise, the TTL checks pointed out that in almost all of the simulations, the same repeating pattern was found: the passers-by move away from the criminals, the criminals follow the passers-by, and the guardians follow the criminals. This pattern is consistent with the trends described in criminological literature such as [3, 13, 23].

Only in some exceptional cases, this pattern was not found. For example, when there are more guardians then locations (e.g., in Section 3 of the appendix in [25]), the guardians may distribute themselves over the locations, so that no crime will ever be performed, and thus no displacement will occur. This case may be compared with the ideal situation that a city has sufficient police force to prevent all crime. Another exception was a situation in which many agents have extreme preferences. For instance, if a certain location has an extremely high attractiveness to passers-by, then these passers-by will stay at that location, even though they run the risk of being assaulted.

7. RELATED WORK

In the literature, a number of modelling approaches exist that have similarities to the approach discussed in this paper.

For example, the work in [17] systematically investigates the geography of crime trajectories using a variety of spatial analysis techniques. However, a difference with the current approach is that these models do not contain an adaptive element (such as an update of reputation), which causes the results to converge quickly to an equilibrium.

[2] the condition t < last_time-δ (where δ is the maximum duration of displacement, for example 6 iterations) was added to make sure that the property does not fail for the end of the trace.

Another approach to analyse the spatio-temporal dynamics of crime is presented in [9]. This approach is based on a Distributed Abstract State Machine (DASM) formalism, combined with a multi-agent based modelling paradigm. Although the agents involved are capable of learning (using a form of behavioural reinforcement learning, where based on past experiences certain preferences are developed that may influence future choices), the notion of reputation is not explicitly incorporated.

A third interesting approach is introduced in [20], which also explores the possibility of simulating individual crime events in order to generate plausible crime patterns. This approach is based on a Cellular Automaton (CA), in which the main elements are offenders, targets, and crime places. Different attributes of the model can be manipulated, among which motivation of offenders, capability of guardians, and accessibility of places. Like the approach mentioned above, the main difference with the current approach is that it does not contain an explicit notion of reputation.

Furthermore, a more specialised approach is presented in [21]. That paper describes a tool to investigate the influence that different police control routes have on the reduction of crime rates. The approach comprises an artificial society consisting of various agents, in particular criminals and policemen. As a follow-up of that work, in [22] the first results are presented that were achieved with GAPatrol, an evolutionary multi agent-based simulation tool devised to assist police managers in the design of effective police patrol route strategies.

Another more specialised approach is put forward in [2]. This approach specifically aims at simulating the process of *deterrence*. A simulation model is presented where each potential offender is part of a social network that consists of several agents. All agents repeatedly face a choice between rule compliance and rule transgression. If agents transgress, they have a probability of being audited and punished. The main aim of the work is to investigate how the probability of being punished influences the amount of crime.

Although all of the papers mentioned above have some similarities with the work presented here, an important difference is that they all focus on simulation only. In contrast, the current paper proposes an approach that combines simulation with logical analysis. Since the simulation traces that result from the LEADSTO environment can directly be used as input for the TTL checker, it is relatively easy for the modeller to verify certain global properties of the model. As such, the paper has many similarities with the work presented in [4], which also combines simulation with logical analysis. However, the domain addressed by the latter paper is completely different (namely the psychological and biological characteristics underlying the behaviour of criminals that are diagnosed with “Intermittent Explosive Disorder”). In addition, that paper does not consider the notion of reputation, nor does it address any notion of adaptivity.

8. DISCUSSION

Investigation of the spatio-temporal dynamics of crime is an important challenge within the field of Criminology. To this end, the current paper presents an agent-based simulation model that can be used as an experimental tool to analyse these dynamics. The simulation model particularly focuses on the interplay between hot spots and reputation, which has not been addressed in earlier work. Using the model, a series of simulation experiments has been performed, under different parameter settings. The results of the simulations have been automatically verified (by means of the TTL Checker [5]) against a number of hypotheses, expressed as logical formulae. In almost all of the simulations, the same repeating pattern was found: the passers-by move away from the criminals, the criminals follow the passers-by, and the guardians follow the criminals. This pattern is consistent with the displacement trends described in criminological literature such as [3, 13, 23].

In fact, one could argue that this is a rather unsatisfactory finding, since it may lead to the conclusion that “the police always arrive too late” (or, more concretely, that decisions to establish new patrol teams, surveillance cameras, and so on, are only made after the hot spots have already emerged). Therefore, an interesting question, which will be addressed in future research, is whether simulation models of criminal displacement can be useful for anticipatory policies (i.e., to increase the number of guardians at locations where hot spots are likely to emerge, instead of at the present locations of hot spots).

Furthermore, note that, although the parameter settings used for the simulation experiments described in this paper were inspired by empirical studies such as [7][3], no effort was put into creating settings that correspond exactly to the characteristics of real cities and populations. Therefore, the results of the presented experiments should not be considered as conclusive about real world situations. Rather, they provide preliminary insight in the process of displacement, and provide support for the usefulness of the presented approach as an analysis tool. For future work, the authors plan to use more realistic parameter settings (including temporal relationships) to investigate to what extent the approach is able to reproduce empirical data.

When such more realistic parameter settings will be considered, also scaling issues will have to be addressed. Although the current simulation model handles population sizes of hundreds of (heterogeneous) agents relatively easily, the simulation time is polynomial in the number of agents. Therefore, complexity problems will arise when populations of (more than) thousands of agents are considered. These problems could be solved by translating the current simulation model to a stochastic model, as is done, for example, in the analysis of epidemics [1]. To make such a translation, the description of the dynamics of a population will shift from a “micro” perspective (at the level of individual agents) to a “macro” perspective (at the level of groups of agents). For example, the number of criminals, assaults and arrests at certain locations may be described by global variables, which are influenced by probabilistic rules. A comparable, but slightly different approach is presented in [4], where the expected number of crimes in certain populations is estimated on the basis of probabilities of opportunities. The main advantage of these types of macro-level approaches is that they can deal with larger populations. An inevitable drawback is however that they imply a loss of detail at the individual agent level. In future work, the benefits of such approaches will be explored.

[3] For example, the authors tried to pick reasonably realistic settings for agents’ preferences and ratios between types of agents.

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