A Model Officer: An Agent-based Model of Policing

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Summary

The way police officers create guardianship is poorly understood, in part because of the complexities of policing. However, in order to understand how to advise the police, researchers must have an understanding of how the current system works. The work presents an agent-based model that simulates the movement of police vehicles, using a record of calls for service to emulate the demands on the police force. The GPS traces of the simulated officers are compared with real officer movement GPS data in order to assess the quality of the generated movement patterns.

KEYWORDS: agent-based modelling, crime, policing, GIS

1. Introduction

The term *guardianship* is a criminological concept that refers to the way guardians, such as property owners and the police, prevent potential offenders from committing crimes (Cohen and Felson, 1979). When potential offenders are choosing whether to commit a crime, they consider how likely they are to be apprehended or stopped by any fellow citizens or police officers in their immediate area (Kleck and Barnes, 2008). The offender's choice to offend is therefore based in part on his or her interactions with other people, and the higher-level crime patterns that result from the choices of all of the individual offenders are influenced by the physical presence (or absence) of police and citizens. Thus, guardianship depends on the spatial, temporal, and behavioural interactions of offenders, citizens, and police officers.

However, the way police create guardianship is not obvious. Policing is a complex, culturally specific process, and officers have many intersecting responsibilities (Policy Studies Institute, 1996). While Robert Peel identified the prevention of crime and disorder as the first goal of policing (Home Office, 2012), police forces are also asked to help with finding missing persons, providing security at public festivals, and handling traffic accidents (Metropolitan Police, 2014). For researchers attempting to influence crime rates by suggesting police policy, ignorance of the way these other commitments constrain officer presence and movement will result in policy suggestions divorced from reality.

Researchers have historically failed to consider these complications in their models of policing and guardianship. Throughout the literature, very few models of guardianship creation exist, and those that do explore it in trivial ways. In general, the issue these models have faced is two-fold: firstly, that many methodologies cannot aggregate lower-level behaviours in order to understand the purposive behaviour of a system comprised of many individuals, and secondly that there is an absence of data that could support such a model. A

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number of simulations emulate the process of officers carrying out responsibilities as part of a larger group, but ignore the many complicating factors, such as the purposeful movement of officers and the fact that they have other responsibilities (e.g. Birks et al., 2012; Groff, 2007). Further, simulated officers are unimpeded by the time-consuming process of actually dealing with offenders (e.g. Melo et al., 2006; Dray et al., 2008) These simplifications significantly bias officer movement patterns, generating patterns of guardianship that do not match the guardianship created by real officers.

In all of these cases, researchers have been hampered by a lack of access to information about officer duties, incapable of incorporating the complexities of policing into their simulations for want of data. As a result of our working relationship with the London Metropolitan Police, we have access to this kind of information. This work presents a simulation which seeks to capture the complex realities of policing, using a combination of data and behavioural research to create a realistic model of police activity. Given that policing is complex, spatial, temporal, and profoundly influenced by human decision-making, we utilise an agent-based model (ABM).

2. The Model

The model presented here utilises an agent-based framework to explore how officers translate their assignments into movement and actions in the context of the environment in which they find themselves. As a methodology, ABM has been particularly successful in incorporating criminological concepts such as routine activity theory (Cohen and Felson, 1979), rational choice theory (Cornish and Clarke, 1987), and crime pattern theory (Brantingham and Brantingham, 1984) into simulations (e.g. Groff, 2006; Birks et al., 2012; Malleson et al., 2012).

In this work, the ABM attempts to capture the behaviours of Metropolitan Police constables, simulating them at the level of the vehicles to which they are assigned. The simulation models the vehicles moving over a road network, specified with $1m^2$ resolution, and are updated on a temporal scale of one minute per simulation step. The model framework is built in Java, using the MASON simulation toolkit, an open-source multiagent simulation library. The following sections will describe the environment in which the vehicles exist, the way vehicles are represented in the simulation, and the way vehicle behaviours are translated into actions

2.1 Environment

In order to represent the environment in which police vehicles exist, the model combines information about the real-world road network with records of calls for service from the community. The model was tested with road network data derived from the Ordnance Survey MasterMap Integrated Transport Network Road (ITN) dataset. The locations of police stations, which factor into the activities of the police vehicles, are taken from the data provided to us by the Met Police. The locations of traffic lights, which impose a time cost on the movements of officers throughout the environment, is taken from data provided by Transport for London (TfL).

In addition to the physical constraints of the environment, vehicles are influenced in how they move by the calls for service that they receive from the general public. The timing and location of these calls for service are drawn from the records of the Call Aided Despatch (CAD) system of the Met Police, and these incidents are used to direct officers to the real-world locations of incidents at the appropriate times. Thus, the pressures and constraints upon the officers are rendered in a simulated setting.

2.2 Agents

The model represents the actions of police officers in terms of the movement and interactions of police vehicles. Vehicle agents have attributes that inform their actions. Table 1 provides an overview of the attributes that characterise the Vehicle agent at any given point in time, specifying the range of values these attributes may take on and providing examples of such values. In particular, Vehicles have a current location in space, a home station, a unique call sign, a current activity, and a current status, as well as a Tasking object.

Table 1. Vehicle attributes

Attribute	Possible Values	Example Value
Current Location	Point in space	(3487, 2387)
Home Station	Point in space	(3487, 2387)
Call Sign	String	EK8N
Tasking	Tasking Object	Response Tasking
Current Activity	Patrolling, Occupied, On Way to Tasking, On Way to Station, Waiting	Patrolling
Current Status	Available, Off Duty, Occupied, Meal Break	Available

All officers obey a daily schedule of returning to their home station every eight hours, to simulate the change in officers. In addition to this shared structure, individual vehicles are assigned to “taskings”, or assignments of duty. The vehicle’s assignment corresponds to the real-world process of assigning officers to carry out different tasks during the day, as is arranged during the briefing before a shift begins. These assignments dictate who will respond to calls, who will focus on patrolling, who will be responsible for coordinating with other officers in order to pick up offenders, and so forth. They structure the officer’s day, and dictate how he progresses from one activity to another. The existing assignments are:

- ***Reporting***: the vehicle is primarily responsible for responding to non-urgent calls for service. It will move around the environment in response to these calls, spending time dealing with the caller when it reaches the site of the incident. The vehicle will spend any unoccupied time patrolling, which is modelled here as moving randomly about the environment.

- ***Transporting:*** the vehicle is responsible for coordinating with other vehicles who have detained suspects. When the Transporting vehicle receives a request of transport, it will move to the suspect and then transport him back to the police station.

- ***Responding:*** the vehicle is responsible for responding to urgent calls for service. When it receives a call, the responding vehicle begins to move at a faster speed and ignores streetlights, both in its calculation of the shortest path and in its movements. When it reaches the site of the incident, it spends time assessing the incident, potentially apprehending an offender. If an offender is apprehended, the vehicle will call for a Transport vehicle and wait until it arrives. It will spend any unoccupied time patrolling.

Figure 1. Normalised heatmaps showing the road usage associated with the real data (A), the random-patrolling model (B), and the tasking-service model (C).

The vehicles communicate with an object called the Despatcher, which informs them of incidents based on the data fed into the simulation and coordinates among the agents, taking a request for transport from a Responding vehicle and transmitting the request to a Transport vehicle. Vehicles plan the shortest path to a point in terms of time, and obey traffic lights except in the case of responding vehicles moving to an urgent request.

3. Results

In order to investigate how the existence of assignments influences the behaviour of simulated agents, we compare two models: one in which all the vehicles spend their time patrolling and receive no calls for service, and another in which vehicles are assigned taskings and receive calls for service as drawn from the real CAD data. The first model emulates the existing ABMs of police movement, while the second represents our contribution.

Figure 1 shows the real road usage data compared with the random-patrolling model and the tasking-service model. Briefly, the real data shows officers making greater use of major roads. The random-patrolling model demonstrates a much less concentrated focus on these roads, while the tasking-service model is more concentrated. However, the tasking-service model is more focused in the south and centre of the region than is the real data. The simulated models generate many more records than exist in the real data, which poses interesting questions about how to compare synthetic versus real data.

4. Conclusions

The simulation generates interesting results, with the behavioural model generating more realistic patterns of road usage than the commonly utilised random movement model. More questions exist with regard to comparing the real data with the generated data, and suggest further investigations into the growing field of ABM validation efforts. The work presented here both addresses the lack of nuanced simulations of policing and pushes forward the practice of inserting real-world data into simulations in order to emulate rich environments for behaviourally complex agents. In the future, this ABM will allow us to explore counterfactual situations, comparing the projected effectiveness of different policing strategies.

5. Biography

Sarah Wise is a postdoctoral researcher in the Department of Civil, Environmetnal, and Geomatic Engineering at University College London. Her research interests include agent-based modelling, social network analysis, data mining, and geographical information systems, and her past research has dealt with crisis situations, health, crime, and social media.

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References

Birks, D., Townsley, M., & Stewart, A. (2012). *Generative Explanations of Crime: Using Simulation To Test Criminological Theory*. Criminology, 50(1), 221–254.

Brantingham PJ and Brantingham PL, 1984, Patterns in crime. Macmillan, New York, NY.

Cornish D and Clarke R, 1987, *Understanding crime displacement: An application of rational choice theory*. Criminology, 25(4): 933–947.

Cohen L and Felson M, 1979, *Social Change and Crime Rate Trends: A Routine Activity Approach*. American Sociological Review, 44(4): 588–608.

Dray, A., Mazerolle, L., Perez, P., & Ritter, A. (2008). *Policing Australia's "heroin drought": using an agent-based model to simulate alternative outcomes*. Journal of Experimental Criminology, 4(3), 267–287.

Groff, E. R. (2007). *"Situating" Simulation to Model Human Spatio-Temporal Interactions: An Example Using Crime Events*. Transactions in GIS, 11(4), 507–530.

Home Officer. (2012). *Policing by Consent.* https://www.gov.uk/government/publications/policing-by-consent

Kleck, G., & Barnes, J. C. (2008). *Deterrence and Macro-Level Perceptions of Punishment Risks: Is There a "Collective Wisdom"?* Crime & Delinquency, 59(7), 1006–1035.

Melo, A., Belchior, M., & Furtado, V. (2006). *Analyzing Police Patrol Routes by Simulating the Physical Reorganization of Agents*. In J. S. Sichman & L. Antunes (Eds.), Multi-Agent-Based Simulation VI (pp. 99–114). Springer Berlin Heidelberg.

Metropolitan Police. (2014) *Specialist Crimes and Operations,* http://content.met.police.uk/Site/specialistcrimeoperations