Analyzing an Offender's Journey to Crime: A Criminal Movement Model (CriMM)

Natalia Iwanski, Richard Frank, Vahid Dabbaghian, Andrew Reid and Patricia Brantingham

Introduction

In the current study we develop a Criminal Movement Model (CriMM) to investigate the relationship between simulated travel routes of offenders along the physical road network and the actual locations of their crimes in the geographic space. Research has shown that a disproportionate amount of crime is concentrated at or near crime attractor locations, which are highly frequented places like shopping malls, parking lots and sports stadiums [1][3][4]. However, attractors have also been theorized to have an impact on the spatial distribution of crime within crime neutral areas. Crime Pattern Theory states that an offender's direction of travel to a criminal event coincides with paths he or she frequently travels on a daily basis such as to work or home [1]. It also suggests that criminals tend to plan their crimes at known crime attractors, and as a result they may select other targets along these routes if criminal opportunities present themselves. Thus it is expected that crimes will be committed along routes between offenders' homes and attractors.

Description of the Model

CriMM was developed to reconstruct the most likely path taken by an offender from their home location to an attractor. These paths are reconstructed to analyze their spatial relationship with crime locations. We make the assumption that most commuters take routes that are the shortest in terms of distance or time, enabling us to use Dijkstra's shortest path algorithm [2]. Given a road network, and home and crime locations of offenders, CriMM generates paths for all offenders. It then identifies the most frequently travelled road segments and calculates the distance of crime locations to generated paths.

CriMM

CriMM Inputs

- Road Network
- Home Location (H)
- Property Crime Location (C)
- Attractor Locations (A_n)

Assigning Attractor for Offender (A_n)

- d(C, A_n)=distance from crime to attractor
- d(H, A_n)=distance from home to attractor
- If d(C, A_n)<d(H, A_n)
  - crime is closer to attractor → attractor A_n is chosen

Generating Path for Offender from H to A_n

- Path= Dijkstra's algorithm run from H to A_n

Calculating Distance Between Crime and Path

- Three Different Distance Measures:
  - Euclidean : shortest straight line distance from crime to path
  - Dijkstra : length of shortest distance route from crime to path
  - Block : number of nodes (intersections) travelled through to get from crime to path

Figure 1: A general outline of CriMM

Assigning Attractors for Offenders

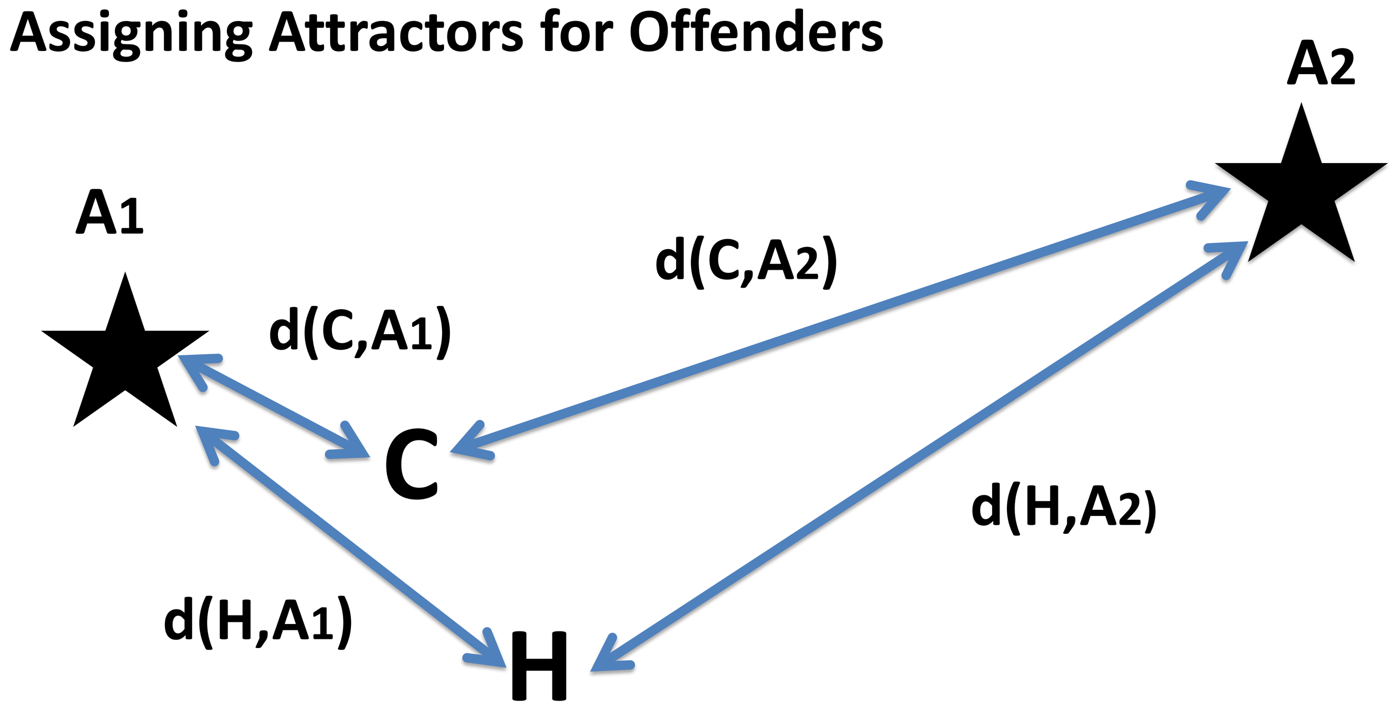


Figure 2: Assigning attractor to offender based on home and crime locations.

Since the d(C, A1)< d(H, A1) for Attractor 1, Attractor 1 is chosen. A path is then generated from the home location to attractor 1.

Simulation and Results

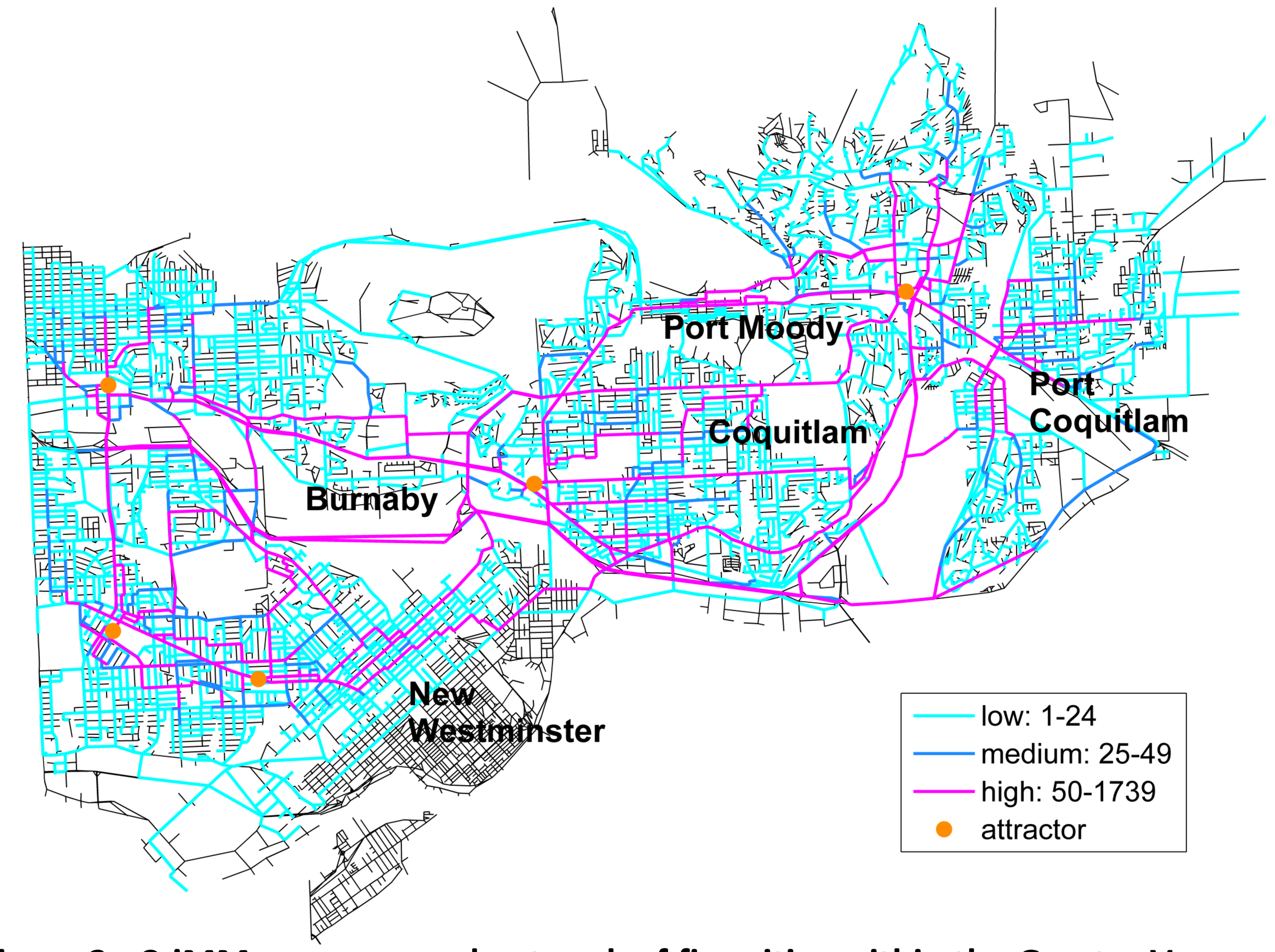


Figure 3: CriMM run on a road network of five cities within the Greater Vancouver Regional District (GVRD) in British Columbia, Canada. 7,807 offenders committing property crimes in the region were included.

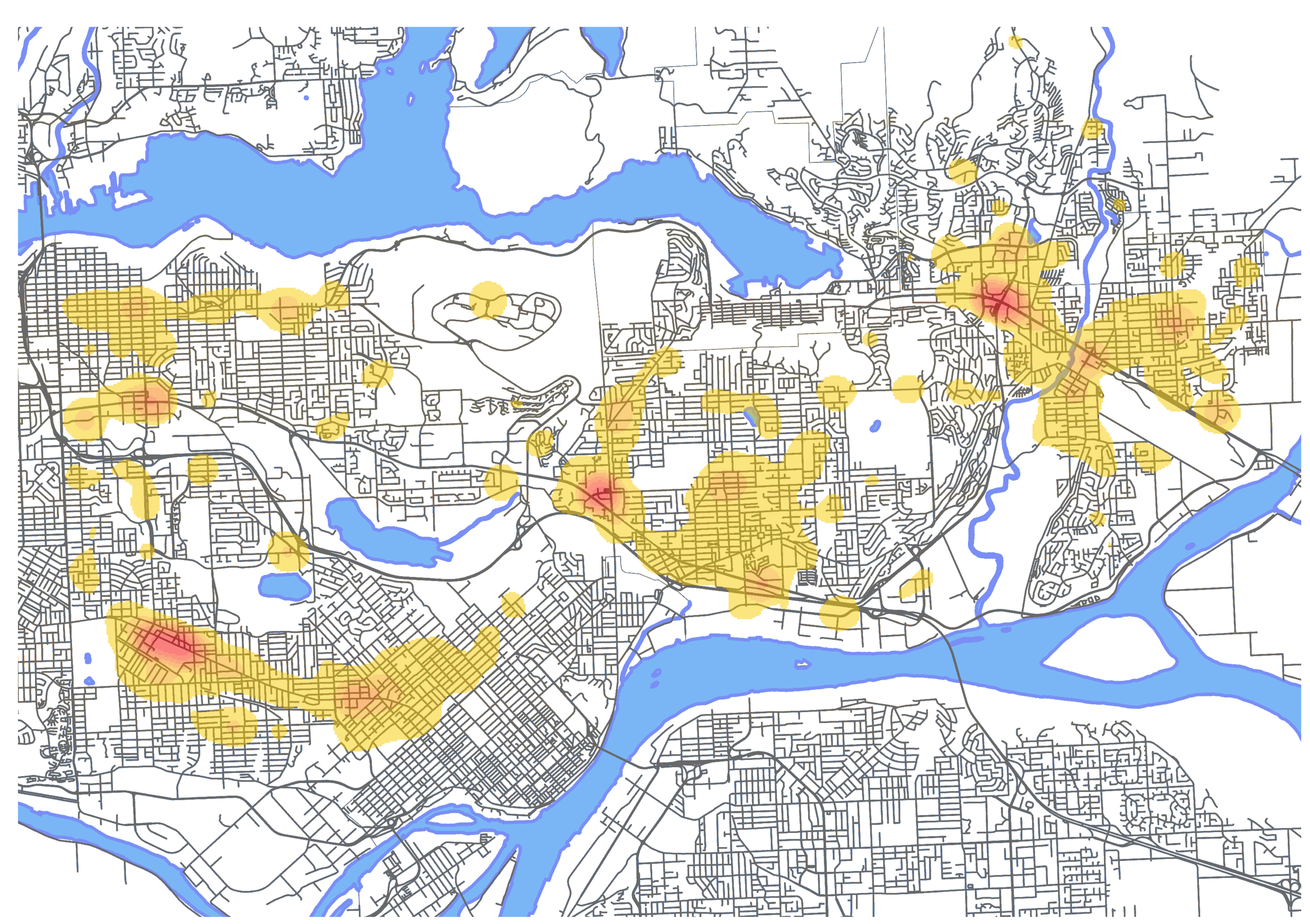
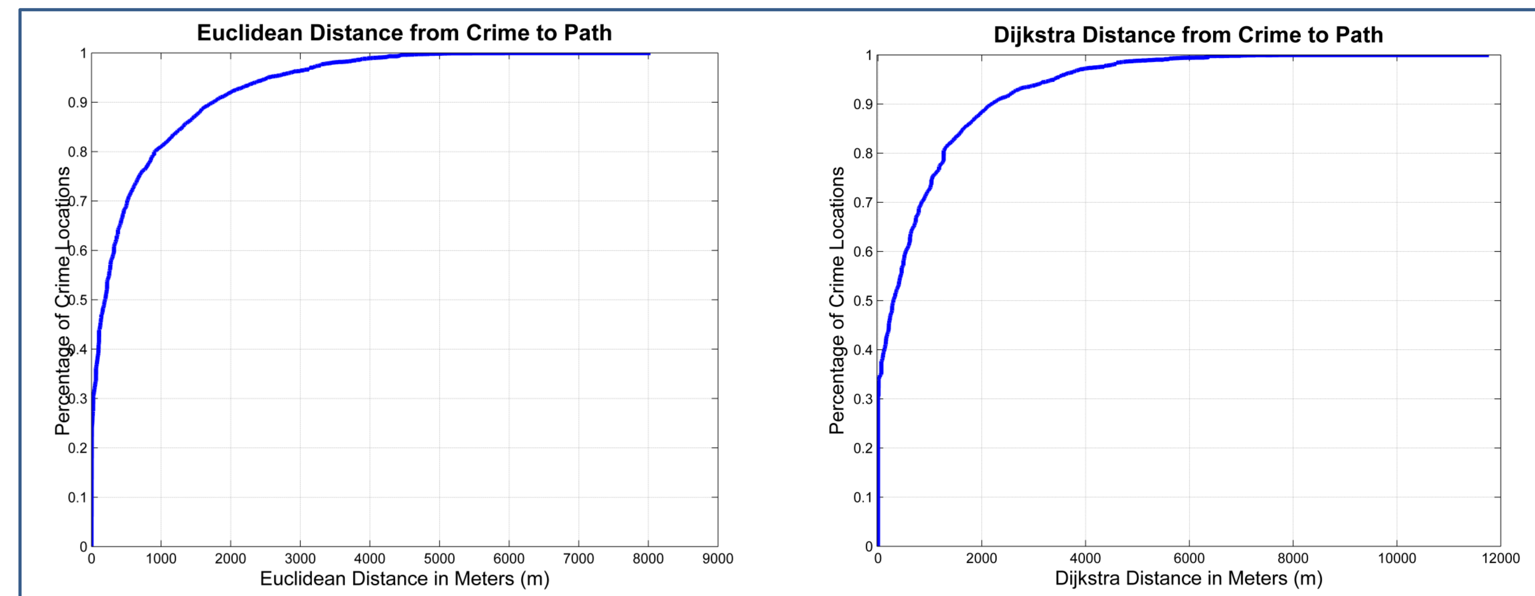
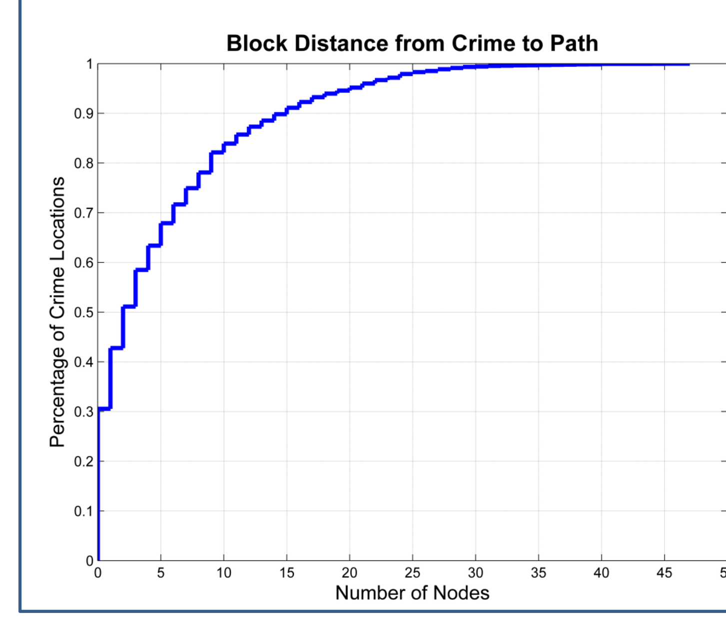


Figure 4: Kernel density map of property crime rates within the five cities studied





Distance from Crimes to Paths using Three Distance Measures		
	Percentage of Crimes (%)	
Distance Measure	30 %	70%
Euclidean	32m	500m
Dijkstra	50m	1000m
Block	0 blocks	5 blocks

Figure 4: Results after measuring the distance between all crime locations and their simulated paths for all 7,807 offenders. As the distance between crime and path increases the percentage of crimes in those categories rapidly decreases.

Discussion

The results highlight the fact that there is an underlying pattern explaining the occurrence of crimes within crime neutral areas. The high percentage of crimes found to occur very close to the simulated paths reaffirms that offenders tend to travel and commit crimes along routes that they are familiar with. Most often they will veer off their path only if a criminal opportunity is nearby and also quite visible, according to Crime Pattern Theory. Results from CriMM can inform police and law-enforcement where to focus crime prevention strategies.

Further Research

Currently CriMM is being extended into a probabilistic model in order to predict the locations of attractors. Starting from each offender's crime location, we extend their path for *n* steps, and create a path based on probabilities assigned to each road segment. These then take into account the general direction of the offender's home to crime vector, and how frequently roads are taken by commuters in the network.

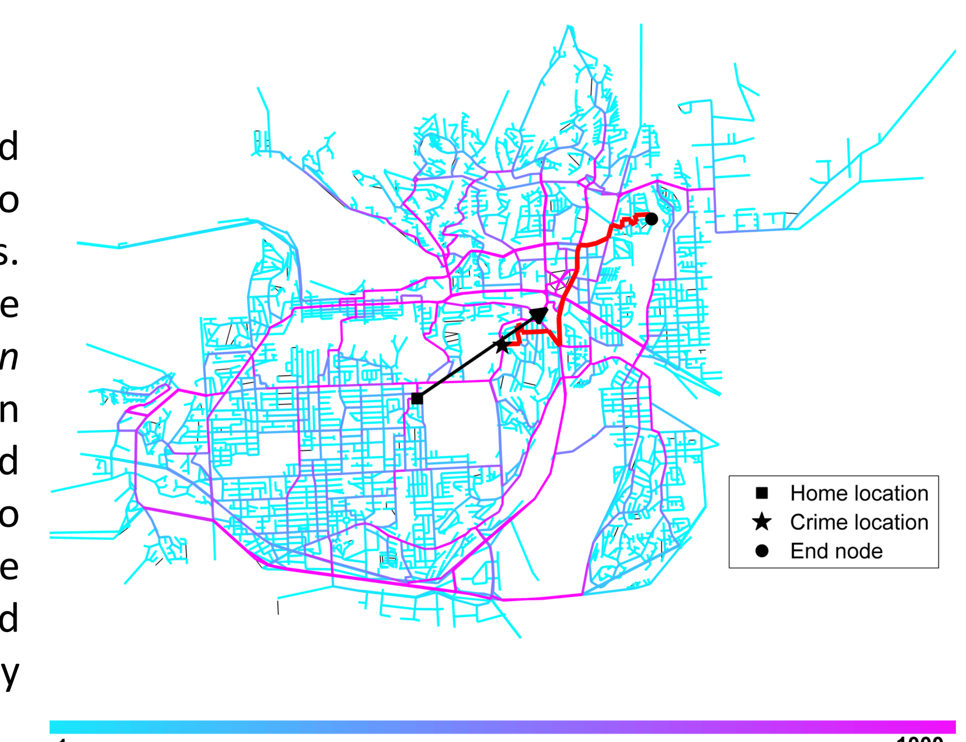


Figure 6: Generating probabilistic path for offender

References

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Acknowledgements

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