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

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***Abstract*— 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 same geographic space. With knowledge of offenders' home locations and the locations of major attractors, we are able to model the routes that offenders are likely to take when travelling from their home to an attractor by employing variations of Dijkstra's shortest path algorithm. With these routes plotted, we then compare them to the locations of crimes committed by the same offenders. This model was applied to five attractor locations within the Greater Vancouver Regional District (GVRD) in the province of British Columbia, Canada. Information about offenders in these cities was obtained from five years worth of real police data. After performing a small-scale analysis for each offender to investigate how far off their shortest path they go to commit crimes, we found that a high percentage of crimes were located along the paths taken by offenders in the simulations. Aggregate analysis was also performed to observe travel patterns in different areas of the cities and how they relate to the amount of crime in each neighbourhood. The results are discussed in relation to both theory and potential policy implications.**

Keywords - Crime attractor, journey to crime, road network, street segment, shortest path

I. INTRODUCTION

In recent years there has been a growing interest to consider the influence of attractor locations on crime in urban areas [7] [19] [20] [21]. While there has been considerable evidence that a disproportionate amount of crime may be concentrated at or near attractor locations [24] [4] [13], there has been a lack of research that has considered the influence of attractors on the spatial distribution of crimes in crime neutral areas. These are areas where crimes are more sporadically distributed with few clusters or concentrations [7]. However, principles of Crime Pattern Theory can be applied to crime neutral areas to gain insight into criminal behavior [6]. This theory states that an offender's direction of travel to a criminal event coincides with paths he or she frequently takes on a routine basis. Thus, although it may appear as though crimes in these areas are haphazardly distributed, the tenets of Crime Pattern Theory suggest that an underlying pattern should be present. Since the target selection behaviour of criminals is influenced by their awareness space, which is largely defined by nodes and paths in their routine activity patterns, it is expected that crimes will be committed along the routes between offenders' homes and activity node locations [6]. While focusing on crime at or near attractor locations is an important task because a considerable amount of crime occurs in the surrounds of these locations, crime neutral areas, too, are important areas of study because they have the potential to reveal patterns about the target selection behaviour of offenders. Knowledge about such patterns may be fruitful in the development of intervention strategies and urban planning practices for the purposes of crime prevention and reduction.

To gain insight into the target selection patterns of offenders, the areas where offenders reside and commit crimes must be analyzed. These areas are often defined in terms of activity and awareness spaces. Activity space, a concept commonly used in human-environment interaction studies, is defined as the area that an individual has direct contact with through the execution of their routine activities [17]. However, it is likely that their knowledge of the environment extends somewhat beyond these limits. All places that an individual has some familiarity with are part of their awareness space [8]. A person's awareness space is likely to be influenced by the principle of distance decay [22]. Specifically, a person will have greater awareness of places geographically proximal to their activity space and lesser knowledge of the environment as the distance from their activity space increases (Fig.1).

Two major components of activity and awareness spaces are nodes and paths. In the course of their daily routines,

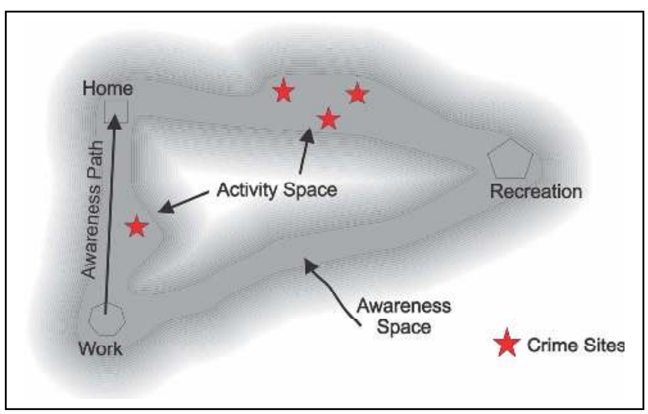

Figure 1. Activity and awareness spaces.

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people move from one activity to the next, spending time at several locations. Home, work, school, shopping centres, recreation sites, and entertainment venues are examples of activity nodes that tend to be amongst our most common destinations [5]. Some activity nodes may be said to have a greater pull or attraction because they draw larger masses of people (e.g., shopping centres and sports stadiums). In contrast, some activity nodes may be said to have a reduced pull because they draw fewer people (e.g., single-family dwellings and stand-alone commercial properties) [15].

Paths such as roadways and walkways are the connections that allow people to travel between activity nodes. The importance of travel paths has been demonstrated in criminological literature. In particular, a variety of studies have considered the physical influence of street networks on the spatial distribution of property crimes in urban environments. Much of this research has concentrated on a small number of characteristics including the relative permeability of neighbourhoods (usually defined by the number and type of roads providing access to and from an area), and the type of road or the amount of traffic flow on roads [3] [18] [26].

The analysis of travel patterns on road networks has also been applied to many different routing problems including efficient ambulance routing [9], optimal timber haulage routes [10], and commuter traffic queries [14]. To address these routing problems, these studies created simulation models along graphs of their specific road networks, and utilized various real-time traffic information and GIS data. In particular the importance of minimizing travel time or travel distance in these case studies requires shortest path algorithms like Dijkstra's algorithm [11] [12] [25] [27].

In determining what types of crimes should be analyzed using Crime Pattern Theory, it is important to note that crimes can be separated into two general categories, those against a specific property, which are usually tied to a location, or those against a person, which are usually not tied to fixed locations [7]. In this paper the focus is on those crimes where the location plays a central role, hence the application of the model is restricted in this paper to only property crimes.

In the current study we investigate the relationship between simulated travel routes of offenders along the physical road network and the actual locations of their crimes in the same geographic space. With knowledge of offenders' home locations and the locations of major attractors (in this case shopping centres), we are able to model the routes that offenders are likely to take when travelling from their home to an attractor by employing variations of Dijkstra's shortest path algorithm. These approaches are utilized to develop a Criminal Movement Model (CriMM) which is subsequently used to run simulations on five attractor locations within the Greater Vancouver Regional District (GVRD), in British Columbia, Canada. With these routes plotted for 7,807 offenders residing in this district, we compare the routes to the locations of their crimes.

The main contributions of our work are as follows:

1) We introduce a model for analyzing spatial patterns on road network data.

2) We use Dijkstra's algorithm for generating paths from homes to attractors, and propose a general algorithm for analyzing the relationship between these paths and crime locations.

3) Our extensive experimental evaluation on real crime data demonstrates the efficacy of the model in analyzing patterns of offender movement within real city networks.

The paper first discusses the development of CriMM in Section II, presents and analyzes the results of an experimental evaluation on a specific city road network in Sections III and IV, and concludes with a discussion of the results, policy implications and future work in Section V and VI.

II. Methods

CriMM was developed to reconstruct a likely path taken by an offender from their home location to an attractor, which represents an activity path in their awareness space. These activity paths are reconstructed to analyze their spatial relationship with crime locations. As a result, the model tests if principles of Crime Pattern Theory can be used to explain patterns in offender movement.

Given a road network and data detailing home and crime locations of offenders, CriMM generates paths for all offenders using Dijkstra's shortest path algorithm, where "shortest" is defined in terms of either travel time or distance. It then identifies the most frequently travelled road segments and calculates the distance of crime locations to generated paths. Three different distance measures are used: Euclidean, Dijkstra and Block distance. Calculating distance in this way allows the model to test if crimes are being committed en route to attractors which would support Crime Pattern Theory.

Part A of this section describes the requirements of CriMM, while Part B explains how CriMM assigns which attractor each offender travels towards. Part C describes how paths are generated for each offender and Part D discusses how the distance between each crime location and its associated path is calculated. The pseudo-code for CriMM is shown in Fig. 2.

A. Model Requirements

As input the model requires information about the road network which, for this model, is encoded into three matrices (Fig. 2, lines 1-3). Each is an n x n matrix, where n represents the number of nodes in the network, and each node is assigned an index i or j where $1 \leq i, j \leq n$. Hence each entry, (i,j), in each matrix corresponds with node i along a row of the matrix, and node j along a column of the matrix. Each of the three matrices is described below:

```
1.   Function CriMM()=(Adjacency Matrix Adj()=(N,E)
2.                     RoadNet_Dist()=(N,ED)
3.                     RoadNet_Time()=(N,ET)
4.                     Crime Location C
5.                     Home Location H
6.                     Attractors A())
7.
8.   //Assigning attractor for offender
9.   Counter = 0 //counting attractors in direction
10.                 of offender's home and crime
11.  for each An in A()
12.    d(C, An)=distance from crime to attractor
13.    d(H, An)=distance from home to attractor
14.    if d(C, An)<d(H, An)
15.      //offender travelling in the direction of An
16.      Counter = Counter + 1
17.    end
18.  end
19.
20.  if Counter = 1  //if only one An is found
21.    SelectedAn = An where d(C, An)<d(H, An)
22.
23.  elseif Counter>1
24.    SelectedAn = An where d(C, An)<d(H, An)
25.                     and d(C, An) is minimum
26.  else (Counter=0)
27.     SelectedAn = An where d(C, An) is minimum
28.  end
29.
30.  //Assigning shortest distance or time path
31.  DistOrTime=rand(0,1);
32.  if DistOrTime>0.5
33.     take path with shortest distance
34.  else
35.     take path with shortest time
36.  end
37.
38.  //Generating Path
39.  P()=path from H to SelectedAn
40.     =Dijkstra(H, SelectedAn, RoadNet_Dist/Time)
41.
42.  //Calculating Shortest Euclidean Distance from
43.  Crime to Path
44.  for each segmentn in P()
45.    EuclidDistVector(segmentn)= Euclidean distance
46.                                from C to segmentn
47.  end
48.  EuclideanDistance=min(EuclidDistVector())
49.
50.  //Calculating Shortest Road Network Distance
51.  from Crime to Path
52.  for each noden in P()
53.    RoadNetDistVector()=Dijkstra(C, noden,
54.                                 RoadNet_Dist)
55.    //RoadNetDistVector()=[node1, node2,…,nodem]
56.    RouteLength= ∑(i=1..m) length(nodei, nodei+1)
57.
58.    DijkstraDistVector(n)=RouteLength
59.    BlockDistVector(n)=|CrimetoPathRoute|
60.  end
61.
62.  DijkstraDistance=min(DijkstraDistVector())
63.  BlockDistance=min(BlockDistVector())
```

Figure 2. General algorithm for CriMM for a single offender.

1. Adjacency Matrix *(Adj)*: Indicates which nodes are connected by a road segment. *Adj(i,j)=0* if the nodes are not connected, and *Adj(i,j)=1* if the nodes are connected.

2. RoadNet_Dist *(D)*: Indicates the length of each road segment in meters. If two nodes are connected then *D(i,j)=length of the segment between nodes i and j.* Otherwise *D(i,j)=0.*

3. RoadNet_Time *(T)*: Indicates the time taken to travel down a road segment in seconds. Travel time is calculated by taking into account speed limit, segment length, and travel impactors. If two nodes are connected then *T(i,j)=travel time between nodes i and j.* Otherwise *T(i,j)=0.*

The adjacency matrix is subsequently used to plot the network. The distance and time cost matrices are used to find the shortest paths from offenders' homes to attractors. The cost matrices can take into account basic characteristics about each road segment including speed limit, length (in meters) and information about travel impactors (for example stop signs or traffic lights).

Also required as input is the location of each crime committed by each offender along with the location of their home when the crime was committed (Fig. 2, lines 4-5). Finally, the locations of attractors towards which the offenders will travel must be specified (Fig. 2, line 6). In reality attractor locations are polygon shapes, however to successfully generate paths using Dijkstra's algorithm, they need to be redefined as points. Thus, a new attractor node at the centre of the attractor polygon is created in the data connecting it to the surrounding nodes (Fig. 3a), or alternatively, a single node which the attractor is closest to can represent the attractor (Fig. 3b).

B. *Assigning Attractors*

CriMM includes an algorithm for choosing the most likely attractor an offender travels towards (Fig. 2, lines 8-28). An appropriate attractor is chosen based on the associated home and crime location characteristics of each offender. The distance between an offender's home location and each attractor, as well as the distance between their crime location and each attractor, is measured. If the distance from an offender's crime location to a particular attractor is shorter than

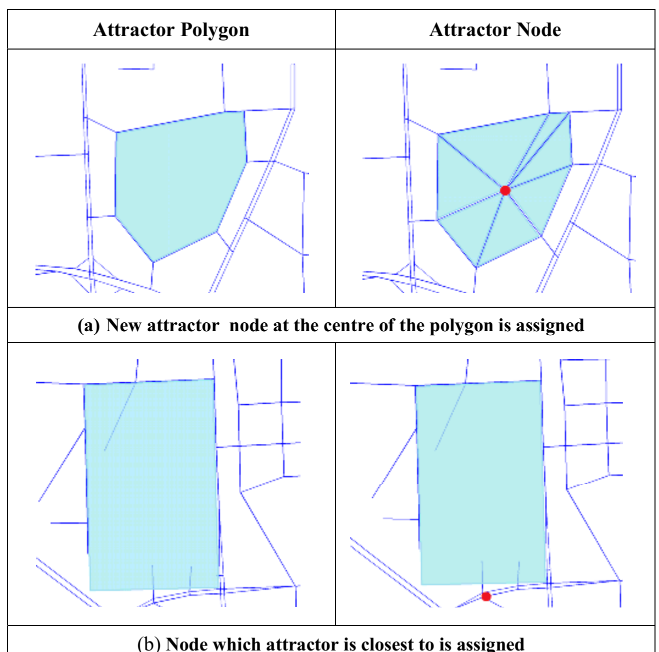

Figure 3. Defining nodes for attractors.

the distance from their home location to the attractor, it is assumed that the offender is travelling in the general direction of the attractor (Fig. 2 lines 9-18). If an offender's crime location is found to be in the direction of only one attractor, that attractor is chosen for the offender to travel towards (Fig. 2 lines 20-21). In the case where the crime location is in the direction of several attractors the attractor to which the crime location is closest to is chosen (Fig. 2 lines 23-25). This is also used in the case where the crime location is never in the direction of an attractor. (Fig. 2 lines 26-28).

In Fig. 4, two attractors represented by black stars are shown, as well as an offender's home and crime location. Since the distance from the crime location to both attractors is shorter than the distance between the home location and the attractors, the attractor that is closest to the crime location is chosen - attractor A. Consequently the shortest path between the offender's home location and attractor A is assigned as the offender's most likely route to their crime.

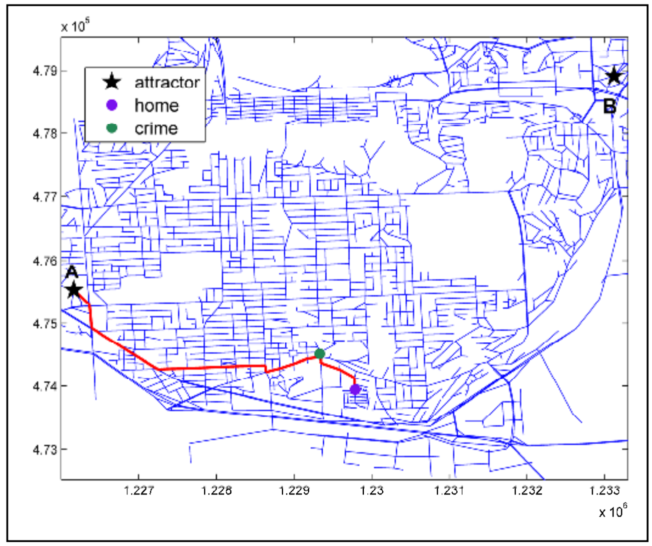

Figure 4. Assigning an attractor for an offender.

C. Generating Paths

Since it was assumed that most offender movement occurs along road networks, the model simulated paths using only road networks. Once an attractor location was decided, it was assumed that an offender would be interested in taking routes from their home to the chosen attractor that are the fastest in terms of time or the shortest in terms of distance. Many transportation studies have made similar assumptions since a path with the shortest distance may not necessarily be the fastest and vice versa [9] [10] [16]. Also, factors like speed limit and number of traffic signs affect the appeal of a route to a commuter or offender. Looking for the shortest path enables the model to use Dijkstra's algorithm.

Once CriMM chooses an appropriate attractor for each offender it then randomly chooses which criminals travel along paths that are the shortest in terms of distance or fastest in terms of time, giving a 50% chance to each option (Fig. 2 lines 30-36). Dijkstra's algorithm is run from all home locations to attractors, generating paths for all offenders (Fig. 2 lines 38-40). All paths are then plotted on the road network and are subsequently analyzed to identify which road segments are travelled most frequently.

D. Crime Locations and Generated Paths

After generating all the paths, CriMM then calculates the shortest distance between each offender's path and crime location using three different distance measures- Euclidean distance, Dijkstra distance and Block distance (Fig. 2 lines 42-63). To obtain Euclidean distance the shortest straight line distance between the crime location and path is calculated (Fig. 2 lines 44-48). To measure Dijkstra distance, an offender's crime location is first snapped to the closest nearby node on the network, and then Dijkstra's algorithm is used to find the shortest route between this crime node and the simulated path. Dijkstra's algorithm finds routes between the crime node and each node on the simulated path. The shortest of these routes is then chosen as the Dijkstra distance which represents the distance that the offender detours from their trip to the attractor in order to commit their crime. Block or node distance is found by counting the number of nodes or intersections that are travelled through to get from the crime location to the path (Fig. 2 lines 50-63).

III. Experimental Evaluation

To evaluate the applicability of CriMM, and to analyze trends in travel patterns of offenders, the model was applied to offenders residing in the Greater Vancouver Regional District (GVRD), located in the south west corner of British Columbia. Both city and offender data were collected and input into CriMM, which was run in MatLab 2009a on a Linux operating system. By examining the relationship between crime locations and generated paths, the model was used to test if principles of Crime Pattern Theory could be used to explain the crime patterns found in the data.

A. Study Area

The GVRD contains 22 municipalities with a population of 2,275,000 [1]. Offender data for criminals residing and committing crimes within three major suburban cities in this district: Burnaby, Coquitlam and Port Coquitlam was included in the model, along with their road networks. The road networks of two additional cities, Port Moody and New Westminster, were also included since they are located in the northwest and southwest corners of Coquitlam respectively (Fig. 5). Consequently many commuters travel through these two cities when travelling throughout the region. However, offender data was not available for Port Moody and New Westminster. Burnaby, Coquitlam and Port Coquitlam are fast-growing cities which contain major commercial centres. Although they experience some level of violent crime, the majority of crime committed is related to property crime and motor vehicle theft [2].

The city of Burnaby is located east of Vancouver, and has a population of approximately 220,000 residents making it the third largest city in the GVRD [1]. Since a major highway, Highway 1, cuts through Burnaby, it has two distinct north and south areas, both with increasing commercial and industrial land use. Its major shopping centre, Metrotown, is located in the southern area and is the largest shopping mall in British Columbia. Surrounded by residential housing, including high-rise apartment buildings, it has become a major crime attractor in the area. Burnaby also contains three more shopping centres: Brentwood, Lougheed and Highgate Mall which were all included as attractors in the model.

Located just east of Burnaby is the city of Coquitlam which has a population of approximately 125,000 [1]. Although it functions mainly as a commuter town for the city of Vancouver, it also has a growing commercial area: Coquitlam Town Centre. This area contains a shopping centre as well as an increasing number of high-rise buildings. The average family income, $82,934, is higher than that of Burnaby's. The city largely contains single-family dwellings [1].

The neighbouring city of Port Coquitlam is significantly smaller with a population of approximately 50,000 and a similar average family income of $87,000 [1]. It too has growing commercial and industrial centres, however Coquitlam Centre still functions as the major shopping centre in the area. Consequently Coquitlam Centre was also included as a crime attractor in the model.

B. Road Network Data

To reconstruct offenders' paths, road network data from the five cities of Burnaby, Coquitlam, Port Coquitlam, Port Moody and New Westminster were obtained from a dataset purchased from GIS Innovations Ltd.[1] The road networks were defined as connected graphs, with edges representing road segments and with nodes representing intersections. Some roads, which in real-life constitute a single road, were divided into multiple segments within the GIS Innovations dataset.

These networks were encoded as shape files and each shape file within ArcGIS had an associated attribute table which provided data for each road segment. The starting and ending node coordinates of each segment, as well as the direction of travel along it, speed limit, length (in meters) and travel impactor information were imported into Matlab as a matrix. Each row k contained the attributes of road segment k, $1 \leq k \leq 11{,}255$, and there were 11,255 road segments in total. The matrix was comprised of 12 columns detailing the desired road segment attributes required by the model.

The attribute tables also included additional information about each road segment that was not used, such as the *type* of road. This information which classifies roads into freeways, arterial roads, collectors, local, etc. could be used in the future, especially when incorporating rush hour traffic situations and other delays. Furthermore, since it was assumed that the road networks used would only include several cities at most, using Dijkstra's algorithm did not significantly increase the computation time of the model.

C. Offender Data

Offender Data was obtained from a collection of databases at the Institute of Canadian Urban Research Studies (ICURS) at Simon Fraser University. These databases contain five years of

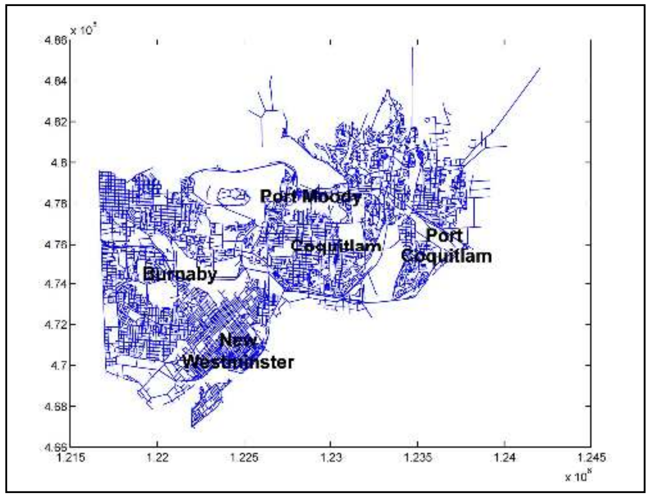

Figure 5. Road network of the five cities included in the experimental evaluation.

real-world crime data for the province of British Columbia from the Royal Canadian Mounted Police (RCMP), Canada's federal police force. Information about calls for service between August 1, 2001, and August 1, 2006 is provided including all phone calls, subjects, vehicles and businesses involved in a crime event and their type of involvement. The specific entries extracted for input into the model were offenders' names, their home locations, crime locations and the type of crime committed. Only offenders residing in and committing property crimes in Burnaby, Coquitlam or Port Coquitlam were included, amounting to 7,807 offenders.

IV. Results

The home and crime locations of all offenders were input into CriMM and the most likely paths taken by these offenders from their homes to one of the five major attractors were then generated. The results of the simulation are shown in Fig. 6 where paths are plotted along a color map to show how frequently different routes were taken. As expected, routes leading up to attractors are highly travelled as well as major routes connecting the cities together.

When these travel patterns are compared with crime rates in

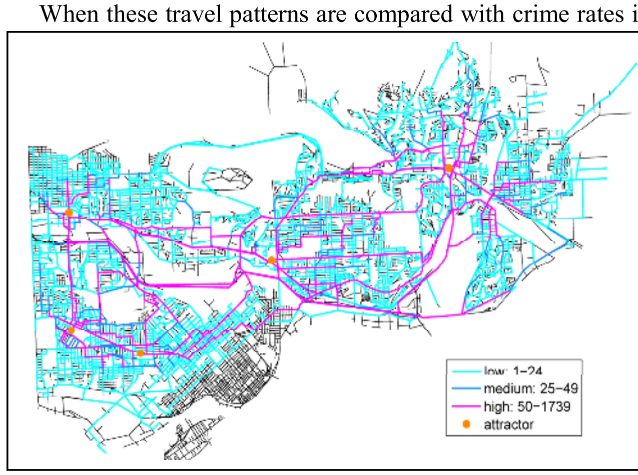

Figure 6. Color map of the paths taken by 7,807 offenders in the experimental evaluation.

[1] http://www.gis-innovations.bc.ca

the region, the routes most frequently travelled tend to correspond with higher crime areas. Fig. 7 shows a kernel density map of property crime rates within the five cities studied. As shown by the darkest shaded areas, the five major shopping centres contain the highest rates of crime. This is an expected result since attractors are known to concentrate crime in their immediate surrounds [24] [4] [13]. In addition, there is an elevated-level of crime observed along routes leading in and out of attractors and along other highly travelled routes. This suggests that routes to attractors may become important components of peoples' awareness spaces and, in turn, may influence offenders to select targets along them.

After generating all the paths, CriMM then compared the location of each offender's crime with respect to their simulated path using the three different distance measures of Euclidean, Dijkstra and Block distance. If a high percentage of crimes were found to be near the generated paths, this would indicate that offenders do tend to commit crimes along paths leading to attractors, and that these paths are part of their activity and awareness spaces.

After measuring the Euclidean distance between all crimes and paths, results were analyzed using a cumulative distribution function (CDF) (Fig. 8) to show the percentage of crime locations that were within a certain distance from each generated path. Approximately 70% of all crimes were found to be within 500m of their generated path, and 30% of crimes were within 32m of their paths. As the distance between crime and path increases, the percentage of crimes in those categories rapidly decreases, reaffirming the notion of distance decay.

However since offenders are travelling along a road network, Euclidean distance is not always an accurate measure of the relationship between crime locations and paths. Road network distance was used to see how far off the path an offender would have to travel to get to their crime location. After analyzing the results using this measure, CriMM output another CDF plot showing that approximately 70% of crime locations were within 1000m of their generated path along the road network. Approximately 35% of crimes were also within 50m of the generated paths (Fig. 9). Similar to the results generated by using Euclidean distance, as the road network distance between crime and path increases, the percentage of crimes rapidly decreases.

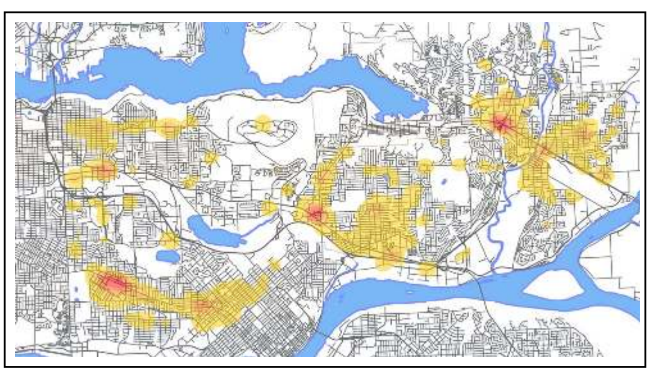

Figure 7. Kernel density map of property crime rates within the GVRD between the years of 2001 and 2006.

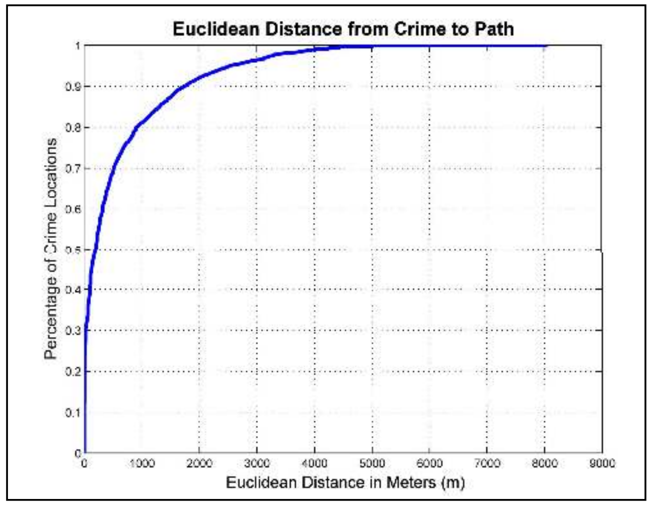

Figure 8. CDF plot of Euclidean distance between all crimes and paths.

To further confirm the results produced with the Euclidean and Dijkstra distance measures, a CDF produced with the block distance measure[2] showed that approximately 68% of crimes were within 5 blocks of their generated paths. Since crime locations were being snapped to the closest nodes on the network, 30% of crimes were actually snapped onto their associated path and thus were 0 nodes or blocks away (Fig. 10).

To ensure that results were not being overly influenced by crime locations occurring at an attractor, experiments were repeated by removing crime locations that were within 300m of the five attractors. This reduced the number of offenders in the evaluation to 6,055. The distance measures still presented the same patterns, however crimes were found to occur slightly farther away from paths. For Euclidean distance 30% of crimes were within 100m and 70% were within 800m. For Dijkstra distance 30% of crimes were within 150m of the paths, and 70% were within 1200m. For node distance 24% of crimes were within 0 blocks and 70% were within 8 blocks.

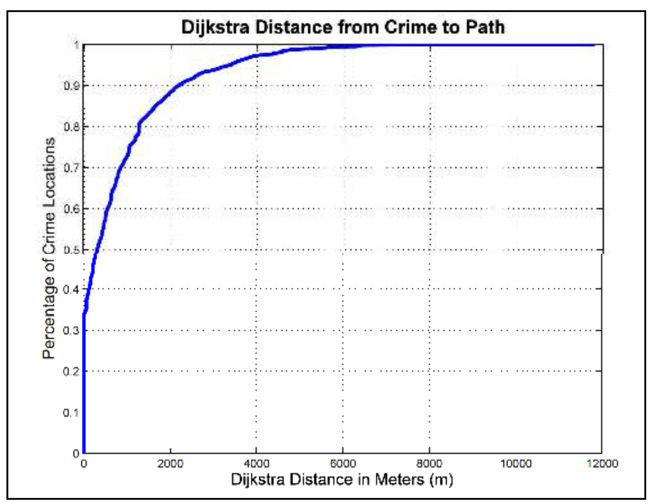

Figure 9. CDF plot of Dijkstra distance between all crimes and paths.

[2] Block or node distance counts the number of nodes in the path between the crime location and the path from home to attractor.

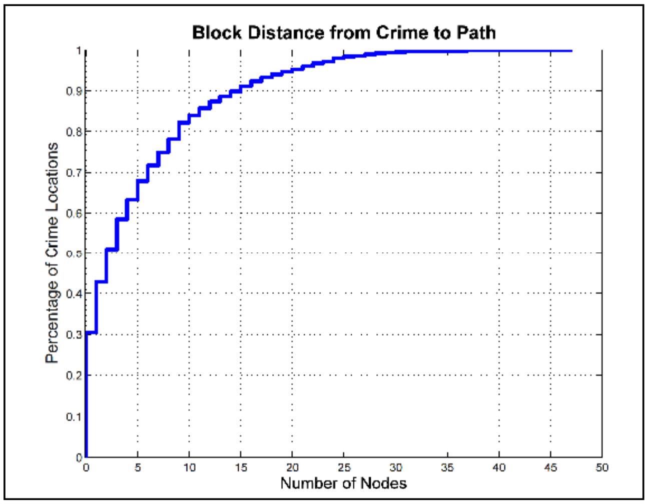

Figure 10. CDF plot of Block distance between all crimes and paths.

V. Discussion and Policy Implications

The results from these distance measures give very strong support for Crime Pattern Theory and 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. Since 30% of crimes were found to be within 32m of their path for the Euclidean distance measure, and within 50m of their path for the Dijkstra distance measure for all 7,807 offenders, a conclusion can be made that offenders do not take lengthy detours off of their path. This can imply that a great deal of offenders will veer off their path if a criminal opportunity is nearby, and also quite visible.

Using this model it is possible to reconstruct a likely path within an offender's awareness space, which plays an important role in the target selection of crimes. The results highlight that offenders do tend to commit crimes in their awareness spaces and more specifically along routes that lead to crime attractors. A limitation of this work is that there may be additional attractors, not accounted for in the current model, that concentrate crimes along the routes to and from the major attractors that were included. Results could be strengthened if different types of attractors were included.

In addition, the current model assumes that offenders' journeys to crime begin at their home and end at an attractor location whereas in real life the journey could start from another location, such as the offenders' legitimate work. Previous journey to crime research has demonstrated the importance of these other locations or nodal points. For example in [23], the directional preferences of burglary offenders were considered. The authors found a strong directional preference towards offenders' places of employment. Specifically, many burglary offences were located near offenders' work locations or along the paths between home and work. If different starting points were added to the current model (like an offender's place of work or school), we could verify the influence of shopping malls as major attractor locations.

The results gained from CriMM can inform crime prevention strategies for law-enforcement since they emphasize that both crime attractors and the major routes between them play a role in criminal activity. By stressing the importance of activity paths in the occurrence of crime, the analysis of crime patterns can be extended to studying the structure of city road networks and the accessibility of crime attractor locations.

This also has direct implications for urban planners since it gives more factors to consider when building new commercial centres. By focusing on property crimes, CriMM directly addresses the types of crimes that are related to commercial success such as theft and break and enter. Better understanding of criminal behavior in relation to urban geography can aid in more informed city planning that may reduce the amount of property crime for citizens and businesses. For example, CriMM can be used by city planners to predict the impact of constructing a new shopping centre on crime in the surrounding area. Since the number of attractors in the model is flexible, attractors can be added or removed to better understand how crime patterns are influenced by the location of attractors.

These results have also shown the capability of CriMM to analyze routes along a city network for a relatively large amount of travelers. Although Dijkstra's algorithm has shown to be impractical on large networks such as province or country road networks [27], it was quite effective on the city-scale analysis conducted in this project. The runtime of the model for 7,807 offenders, without measuring the Dijkstra distance between crimes and paths was approximately 4-5 hours. Including the Dijkstra distance measure significantly increased the runtime since Dijkstra's algorithm was not only used to generate paths between a home and attractor location, but also between each offender's crime location and each node along their path. With the Dijkstra distance measure CriMM took approximately 40 hours to run.

VI. Conclusions and Further Work

This project developed a model that would reconstruct the most likely routes taken by offenders to their crime locations. By using Dijkstra's algorithm, and taking into account key locations tied with a criminal event, CriMM was used to analyze the occurrence of crime in crime neutral areas displaying results consistent with Crime Pattern Theory.

Since this project has proven it is possible to reconstruct certain awareness paths of offenders, in the future it may also be possible to reconstruct more activity paths and ultimately offenders' awareness spaces. Crime locations can then be linked to individuals based on which particular awareness space they are found in. By being able to understand the relationship between geographic characteristics of offenders' activity spaces and their crime locations, it could be possible to identify perpetrators of criminal events. In combination with other types of investigative techniques, offenders could then be arrested and charged, contributing to local crime reduction.

In future versions, the Dijkstra distance measure could be optimized by reducing the number of nodes the crime location is compared with, however this would also introduce some degree of error into the model. For larger networks and for situations that require a very high number of shortest path calculations Dijkstra's algorithm could be replaced with a more efficient algorithm [12] [25] [27]. However for the current model this was not a major necessity because of the smaller scale of the road networks.

CriMM could also be extended to analyze crime patterns in other cities to see the role of geography in Crime Pattern Theory, and results for different crime types could be generated and compared. A sensitivity analysis could be conducted to analyze how crime patterns change if attractors are added to the model or their locations are changed. It would be possible to investigate the degree to which paths change and also highlight new areas where crimes would be likely to occur. Comparing the paths generated by CriMM with general traffic patterns would also lend some more insight into the choices of routes that offenders make.

In this paper, attractor locations were assumed to be shopping centres and were the predefined end locations for offenders. In the future this restriction will be relaxed since CriMM is being extended into a predictive model, where based on an offender's home and crime location, one can determine where the offender was headed. In addition, factors like traffic delays can be implemented into the model to see how the presence of different obstructions and heavy traffic can affect offenders' routes. In this way the dynamic nature of a city road network can be taken into account.

By using current data to understand patterns in criminal behaviour this model is anticipated to help criminologists, police and policy makers focus their attention on key areas that are frequented by offenders. It also confirms that there is an underlying explanation for the occurrence of crime within crime neutral areas. The strong results obtained with CriMM highlight the importance of continued research on attractors in relation to Crime Pattern Theory.

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