Development of an Artificial Intelligence System for Detection and Visualization of Auto Theft Recovery Patterns

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ABSTRACT

Auto theft is the most expensive property crime that is on the rise across the nation. The prediction of auto drop-off locations can increase the probability of offender apprehension. For successful prediction, first the patterns of thefts are identified. Then, a prototype expert system successfully identified embedded drop-off location clusters that were previously unknown to investigators. The system was developed using the expert knowledge of auto theft investigators along with spatial and temporal auto theft event data. Drop-off clusters were identified and validated. A map interface allows the user to visualize the feature clusters and produce detailed reports. Such GIS applications give us the ability to attain a geographical perspective of incidents within the community, thus help law enforcement officers discover the patterns of incidents and take necessary measures to prevent them.

Keywords: ArcIMS, auto theft and recovery, crime mapping, data sharing, GIS, hot-spot analysis, pattern discovery.

1. INTRODUCTION

According to a recent statistics, every 20 seconds a motor vehicle is stolen in the United States. Law enforcement officers work daily to locate and retrieve stolen cars, while insurance companies spend billions of dollars each year compensating owners of stolen vehicles. Auto theft incidents may have complex and varied patterns due to very different objectives such as for auto parts, joy rides, and use in other crimes; thus, computer aided crime analysis tools are required to cop with this crime that is on the rise nationwide.

One of the main goals of crime analysis is to identify and generate the information needed to assist in decisions regarding the deployment of police resources to prevent and suppress criminal activity (Goldsmith *et al.* 1999, Mena 2003). Computer spot maps are very difficult to use especially when there are many crime events, as in auto theft, the number of spots plotted becomes hard to interpret. This creates even more confusion when crimes over a long time period are plotted. The high density of crime places increases map clutter and makes interpreting the underlying patterns of events more difficult. In addition, repeat-crime and one-time crime places receive the same degree of attention.

Hot-spots are places that have shown persistent tendencies to be sites of crime (Goldsmith *et al.* 1999; Levine 2000, Mena 2003, Hick *et al.* 2004). Discovery of hot-spots is a critical task because the deployment of police and other prevention resources at these hot-spots makes the greatest contribution to crime.

Cluster analysis can be an effective method for determining areas with high concentrations of crime (Grubesic and Murray 2001). For auto theft events, since the number of potential targets is large, another alternative to prevent auto theft, even though indirectly, is to capture the criminals at the place of the drop. Detecting either form of hot-spots is important to identify the concentrations of incidents, which can help focusing police and community resources on these areas (Levine 2000). However, it is a particularly challenging task to detect hot-spots by clustering analysis due to the uncertainty of the appropriate number of clusters to generate and the significance of the found clusters (Grubesic and Murray 2001). In other words, how many clusters the analyst will be looking for is difficult to estimate. Moreover, for example, if the analyst dictates that ten clusters should be found, it is not guaranteed that all of the ten clusters will truly correspond to hot-spots. The question is, then, which clusters are significantly suspicious compared to others.

In this work, while avoiding these two big challenges of cluster analysis for hot-spot detection (Grubesic and Murray 2001), we have managed to develop a scalable tactical crime analysis tool for auto theft events, specifically for identifying and predicting drop-locations through a cluster analysis approach. In this work, the analyst does not have to specify how many clusters to be found; instead, the analyst is supposed to define what makes a cluster a set of related events. For example, auto theft detectives we have met in Orange County Sheriff's Office agree on the fact that each thief has preferred types, makes, models and years of vehicles to steal and drop-locations based on the means of transportation and where he/she lives/works and where he/she may feel comfortable dropping the stolen vehicles, etc… Although, the process of deciding what should make a cluster a real cluster may seem to be a detailed and involved one; in reality, the analyst always knows what he/she is looking for in the data. In fact, it is somewhat unnecessary and meaningless to ask the analyst for the number of clusters to be found, compared to asking what to find. After all, the analyst's answer to the question above would most likely be: "Find the significant clusters; do not care how many!" (Grubesic and Murray 2001).

Based on the size and the recency of the clusters found, what an analyst can accomplish is one or more of the following but not limited to: (1) Assign police officers to patrol the current most preferred drop locations to catch criminals at the time of the drop; (2) Identify what are the most common trends of the recent auto thefts, such as discovering that most preferred drop-locations are shopping malls, etc.; (3) Further analyze these groups of related (linked) events by using additional non-numerical clues available in the records to the analyst which may not be readily usable by the computers due to lack of corresponding technology (e.g. notes taken by the police officers in natural language form will not be usable by computers until natural language processing solutions are well-developed); (4) Conducting security surveys at stores and residences in hot-spot areas, helping them decrease their chances of victimization (Bruce, 2004).

2. DATA COLLECTION

A major obstacle that prevents the practical use of artificial intelligence type analysis in crime analysis is the ability to develop a user interface and automated data gathering tools that allows a crime analyst to use it in the job setting (Schmerler *et al.* 2004). An objective of this research is to deliver a tool, which can be used by auto theft detectives and crime analysts in the workplace. A detective is typically not going to be interested in the particular algorithm used to provide insight to the crime patterns. What they will desire is the ability to have information and tools that can help them solve crimes that are both usable and accessible (Bruce, 2004). Providing these tools requires access to the data to perform the research necessary to select appropriate methods and the ability to translate them into a computer software application.

We collected our simulation data from Crimenet on auto theft events that took place in Orange County from January 2002 to April 2003. A map of Orange County is shown in Figure 1.

For our early experiments and demonstrations, we mapped the auto theft incidents on an L-shaped polygon as will be shown in Figure 2.

Crimenet is a basic reporting, information, and intelligence system for use in crime analysis. Crimenet is a group of subsystems, including Crimemap, Bulletin Management System, and other crime-related applications. While Crimenet and Crimemap have similar names, Crimenet refers to the entire system, and Crimemap refers specifically to the crime mapping application. At its basic level, it is a series of query-based reports that return information gathered from various sources within the Orange County Sheriff's Office. These sources are data entered into the Tiburon RMS (Records Management System), data collected in spreadsheet format by the Crime Analysis Unit, and Legacy data from the CARS EMS system.

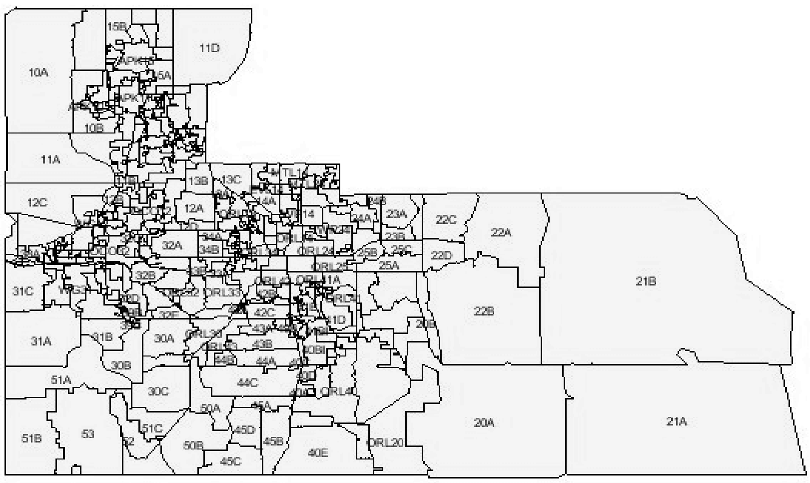

Figure 1. A map of Orange County and its division into 30 zones

The entire Crimenet system is accessible through the Oracle-based Orange County Sheriff's Office Portal web site. The system makes use of two primary elements within the Oracle system; Portal's ability to define and generate reports and forms, and the ability to program customized reporting using PL/SQL. All code, reports, forms, tables, and views are stored within the Crimemap schema on the Oracle Portal server. To allow flexible reporting, Crimenet converts data from the various sources to a richly structured database schema stored within the Crimemap schema on the server. Reports are then built to display this data in a format required by the Crimenet users. Tiburon data is accessed both directly (in reports where up to the minute data is required) via a database link, and also via a shadow database, which has been indexed to allow for faster access to specific reports.

The dataset we used for our preliminary simulations have approximately a thousand auto theft events. This is a small fraction of all the events we have in our database because the rest of the entries do not have a matched address that could be converted into numerical (X, Y) coordinates. The X and Y for the recovery addresses are generated by a geo-coding server. In our experiments, for X and Y coordinates, we used UTM (Universal Transverse Mercator) coordinates. UTM is a planar coordinate system, which simply measures in meters east and north from two perpendicular reference baselines (Hick *et al.* 2004). However, spherical (latitude/longitude) or any other coordinate system would be equivalently useful. The geo-coding server used here is ARCIMS, which is currently used for the Crimemap system. Each event is characterized by the following five features: Make of the vehicle, Year of the vehicle, X and Y coordinates of the recovery location, Date of the theft.

Make of the stolen vehicle is a unique numerical value for each different make. In our dataset, we had 62 different makes of vehicles. Year of the vehicle is a numerical value ranging from 1970 to 2003. The (X, Y) coordinates are UTM coordinates (real numbers).

3. PATTERN DISCOVERY

To be able to understand the underlying dynamics and patterns of criminal activity, a visualization tool is needed. In order to combat the complexity of the crime spot maps, due to the increasing number of spots, we developed an animation tool that visualizes the criminal activity on a daily basis. This animation tool creates a movie of the criminal activity, where each frame contains auto thefts committed in a day. Such a tool has been used to analyze the spatial and temporal dimensions of gun recoveries by the Bureau of Alcohol, Tobacco and Firearms and shown useful (Freeman 2002).

However, the amount of daily activity can still be too complex to display in one frame because the analyst might not be able to make sense out of the high number of spots being displayed (see for example, Figure 2). Therefore, we developed an algorithm to cluster events that have similar patterns, thus breaking down the complexity of the set of all events by partitioning this set into clusters. The commonalities that our algorithm identifies are the kind of commonalities that auto theft detectives would look for in these events. Consequently, our algorithm automates the laborious manual process that these detectives have to go through.

An example of the commonalities among events that our algorithm recognizes is the similarity of the recovery locations and vehicle makes, as illustrated in Table 1 and Figure 3. These commonalities are not very straightforward to detect. In Table 1, some details of five auto theft events are given. For example, even though event number five has shorter physical distance to event number one (similar recovery locations), they belong to different clusters because the makes of these vehicles are different. That is why a mathematical framework is needed to measure commonalities among events.

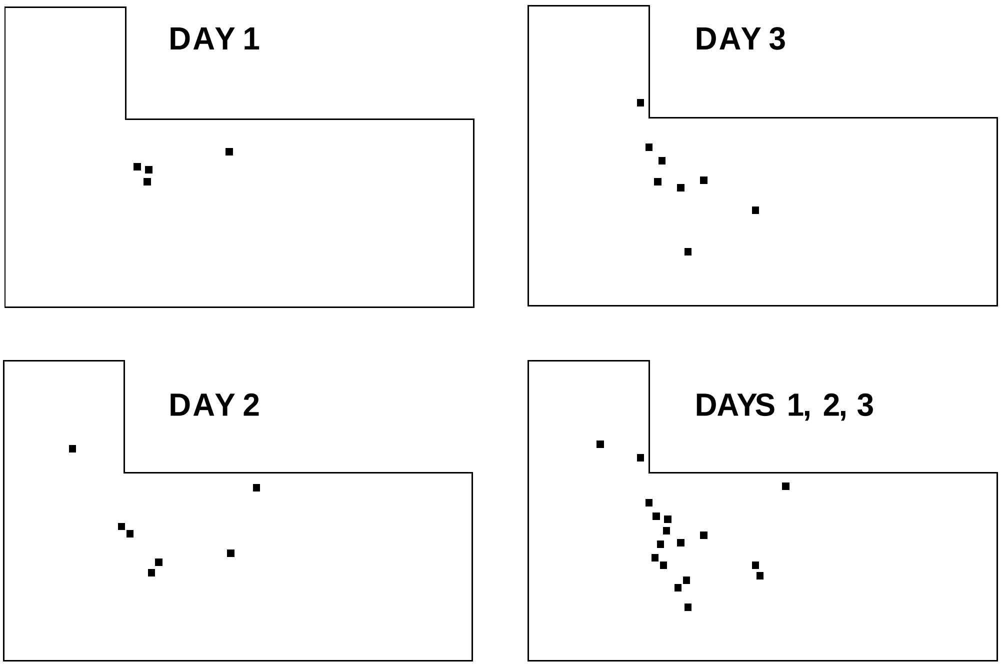

Figure 2. Auto theft incidents in Orange County for three consecutive days in 2002, where each frame contains many events with different patterns (specifically the make and the year of the stolen vehicles). For the sake of simplicity, for these early experiments, we used a simple L-shaped polygon

as the Orange County map to easily visualize the auto theft incidents. Our animated map creates frames labeled "Day 1", "Day 2", "Day 3", etc… In these three frames, all the corresponding daily criminal activity is displayed. In the frame labeled "Days 1, 2, 3", all the criminal incidents of these three days are superimposed onto an ordinary map to demonstrate how quickly unanimated maps may get useless and unreadable.

Event ID	**X**	**Y**	**MAKE**	**Cluster ID**
1	1.1	3.4	FORD	+
2	1.0	0.8	HONDA	*
3	4.5	2.1	TOYOTA	-
4	0.7	2.0	FORD	+
5	1.9	2.4	HONDA	*

Table 1. A simple demonstration of the clustering technique.

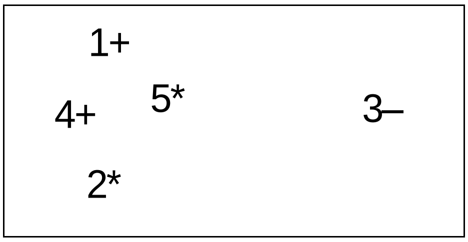

*Figure 3. Grouping events similar in feature space. The symbols represent the event and the cluster ID. There are five events that make three distinct clusters denoted by the *, +, – symbols. The position of these symbols represents the recovery location of the vehicle.*

To measure how similar two given auto theft events are we define a distance measure between them. This distance measure is based on a weighted Mahalanobis distance measure (Eq. 1), where the weights, *w*, for each feature *i*, are determined by the domain expert.

$$Dist_{X,Y} = \sum_i \left(w_i \cdot \frac{\left| X_i - Y_i \right|^2}{\sigma_i^{\,2}} \right), \qquad (1)$$

In (Eq. 1), X_i and Y_i represent the value of the i^{th} feature of the incident *X* and *Y*, respectively. The standard deviation of the feature *i* is denoted by σ_i. Since the weights are only relative, it is not challenging to come up with a suitable assignment for them for the task to be accomplished. For example, if the spatial proximity is much more important than temporal proximity, then the weights of X and Y must also be much higher than the weight of the Date of the theft.

Mahalanobis distance involves in its definition the standard deviations of the features. This is necessary because the variation in a feature with a low standard deviation is more significant than the same amount of variation in a feature with a high standard deviation.

The basic idea behind a clustering algorithm is to group together the events with a high degree of similarity amongst them (small inter-distances). The null hypothesis is that all the auto theft incidents are independent of each other (the distribution is perfectly random). Our approach is closely related to the nearest neighbor measure (Grubesic and Murray 2001), where each new incident is placed in an existing cluster, if it is the nearest cluster to the incident and the distance from the incident to the cluster is smaller than or equal to a predefined threshold value. Otherwise, the incident is placed in a newly created cluster. The threshold is a simple function of the average distance of all the data points as shown in Eq. 2.

$$Threshold = AverageDistance \cdot Sensitivity \qquad (2)$$

The sensitivity is the desired deviation from the null hypothesis. When the sensitivity is set to zero, only repeat-crime activities (exact same pattern and location) are clustered. If it is set to an extremely large value, most of the incidents will be considered to be related. Our experiments showed that the sensitivity should be kept below 0.5 to get feasible clusters (it can be even smaller based on how compact clusters are desired).

Determination of the value the average distance of all the data points does not necessarily require having all the data points in hand. In fact, it only requires some reasonable number of data points to initially estimate the AverageDistance, which is to be re-estimated as more data points are entered to keep it up-to-date.

Thus, our approach does not require a priory specification of the number of clusters to be found. Instead of asking the user-define how many clusters to be found, which brings significant subjectivity into the analysis (Grubesic and Murray 2001); we take advantage of knowledge and experience of auto theft detectives to decide the criteria for clustering. Furthermore, there are no established methods in the statistics literature to determine the appropriate number of clusters (Grubesic and Murray 2001).

To increase the robustness of our clustering algorithm, we also use an upper-bound for the differences of features if two events are to be placed in the same cluster. To illustrate this, consider two events that are a year apart but very similar in other aspects. With a proper selection of the upper-bound for the difference of the dates of the events, we prevent our clustering algorithm from assigning these two events into the same cluster. Such an upper-bound is necessary for a tactical crime analysis, in order to guarantee that two events so far apart in time are indeed grouped into different clusters. However, if desired, the upper-bound can be discarded and the weights can be adjusted to fight such criminal activities. For example, the two events mentioned above can be identified to be in the same cluster even if they were 10 years apart by setting the weight of time to zero and removing the upper-bound.

In our approach, to be able to use such a mathematical framework, each event has to have a fixed number of features. These features have to be numerical. For example, a location has to be converted from an address to an (X, Y) ordered pair. For simplicity, we do not consider incorrect or missing information. These issues will be addressed in Discussions. A brief pseudo-code of our clustering algorithm is given below.

For each new entry *N*,

i. **For** all clusters, find D_i: the distance of *N* to the i^{th} cluster

ii. **Set** *D* equal to D_m: the minimum of D_i

iii. **If** *D* is not greater than the threshold in (Eq. 2) then *N* belongs to the cluster *m*

Else, a new cluster *C* is created and *N* is placed into the cluster *C*

4. MAPPING AND VISUALIZATION

We use Oracle 8i to store and manage the auto theft data, each record of which is associated with a spatial column computed from X/Y coordinates. Each X/Y coordinate pair is geocoded from the address field of each auto theft record with ArcIMS, an ESRI GIS product that is also used to visualize and publish the auto theft data online. Another ESRI product ArcSDE, A Spatial Data Engine, is used as a gateway to access this data by ArcIMS. Web Server (Microsoft IIS 4.0), ArcIMS and Oracle form a three-tier architecture that eases data visualization and publishing. Whenever users operate on the map (for example, when a data point on the map is selected, or a query tool in the toolbar is used, or the map is zoomed in/out), the browser (the client) will send the request to the Web server, which then forwards the request to the ArcIMS Server. The ArcIMS Server queries the data stored in Oracle database via ArcSDE. Once the query is done, ArcIMS sends the result (generally a JPEG image) to the Web Server, which then sends the JPEG image to the browser.

On the map interface, three relatively big clusters are shown in Figure 4. For convenience, each event is assigned a short string (A, B, C, etc) by a simple hashing function so that the user can observe the theft and drop/recovery locations of vehicles. A red circle corresponds to a theft location and a blue rectangle corresponds to a recovery location. Using the tools on the left panel, the user is able zoom in/out, select data points, run queries to display only certain points, measure the distance between data points, etc…

In Figures 5 and 6, we demonstrate the use of the interface by zooming in on two exemplary auto theft events identified to be in the same cluster by our algorithm. The user can be automatically informed on the existence of such suspiciously similar patterns of criminal activity with a click of a button. Thus, using this interface with our algorithm allows the police officers easily decide which areas to patrol. Any auto theft even near points N and M (shown with circles) is very likely to be dropped somewhere near points N and M (shown with rectangles).

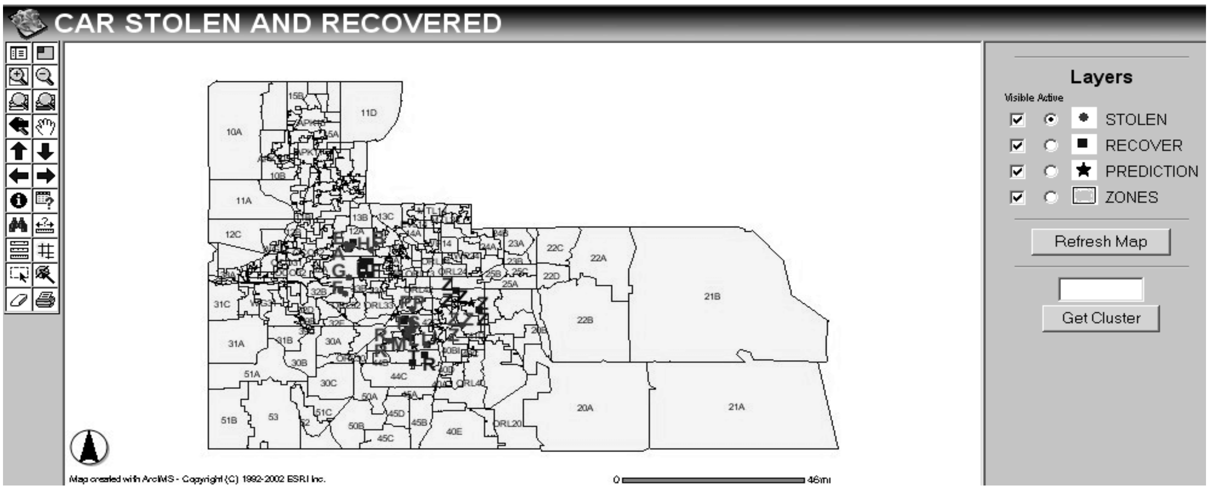

Figure 4. The map interface for data visualization.

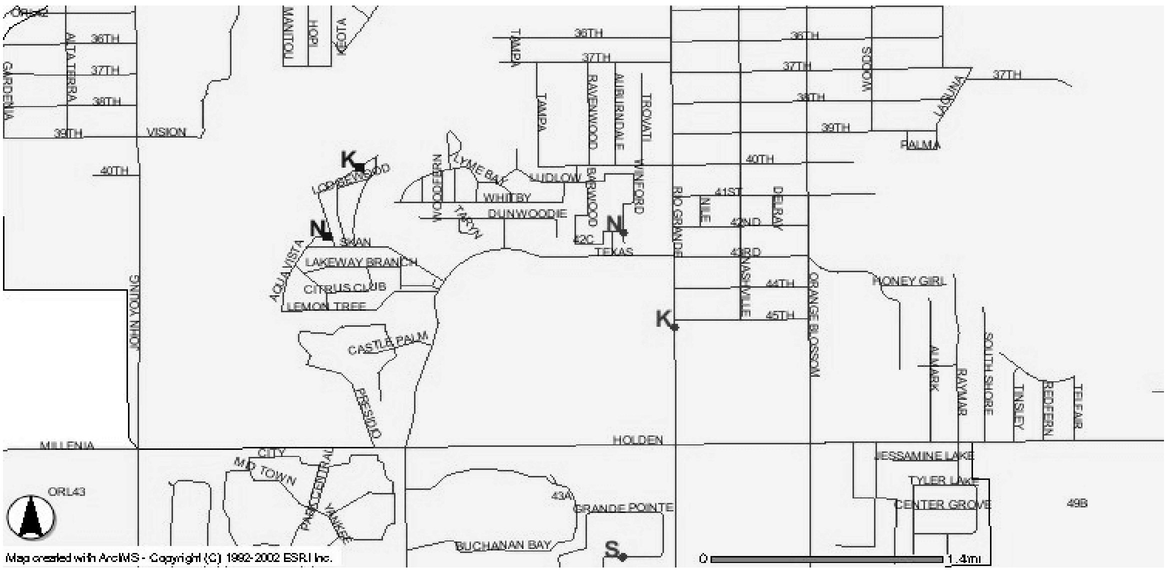

Figure 5. Zoom in on two exemplary incidents identified to be in the same cluster.

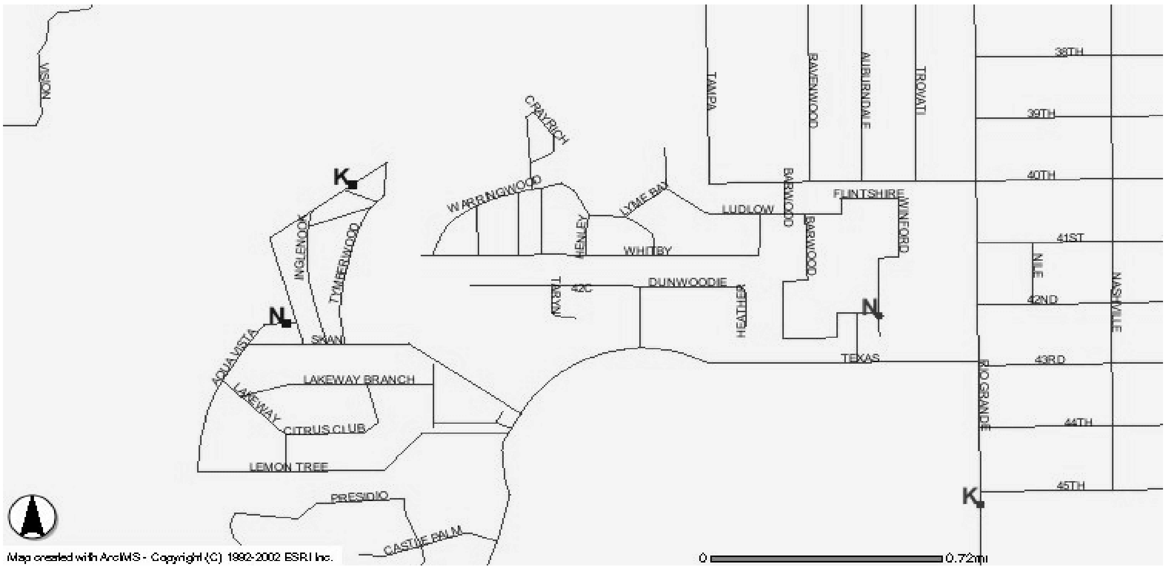

Figure 6. Zoom in more on the exemplary incidents shown in Figure 5.

5. SIMULATION RESULTS

The weights and the upper-limits of the features for the calculation of the distance measure are shown in Table 2. As expected, the clusters found by the algorithm show orderly features such as specific drop-locations for a specific make and years of stolen vehicles (see Table 3). When viewed by our animation tool, each cluster is a collection of auto thefts local in time and recovery location. Breaking down a set of events by such sequences demonstrate spatio-temporal patterns that are often more predictably reliable than those discovered by static statistical methods (Helms 2002) because the local patterns may disappear when looking at the global statistics.

As a verification of the quality of our results, we also show the model of the stolen vehicles in the last column of Table 3. Although the model information is not used in the simulations (the algorithm has no hint of the model of the vehicle), some of the clusters are composed of not only the same make but also the same model of the vehicle. In addition to the five fields available in the dataset, every record in a cluster is given an ID number to ease references to specific records.

Feature ID	Description	Weight	Upper-bound
1	**Make** of the vehicle	20.0	strictly only one make in a cluster
2	**Year** of the vehicle	2.5	10 years
3	**X-coordinate** of the recovery location	15.0	Not used
4	**Y-coordinate** of the recovery location	15.0	Not used
5	**Date** of the theft	10.0	60 days

Table 2. The features, weights, and upper-bounds in the simulation dataset. The values of the weights and the upper-bounds are chosen based on empirically the suggestions of the Orange county Sheriff's Department detectives.

As seen in Table 3, this cluster consists of Honda Accords, with the record number three as the only exception. Our further experiments show that with a more strict similarity measure (greater deviation from average), we can purify the clusters. In that case, the above cluster will have only the "Accords"; however, the total number of clusters will increase. Therefore, this is a decision to be made based on the specifications dictated by the analyst.

ID	X-coor	Y-coor	YEAR	MAKE	DATE	MODEL*
1	504071	1540191	1994	HONDA	10/10/02	ACCORD
2	506029	1543959	1996	HONDA	10/11/02	ACCORD
3	501894	1544772	1997	HONDA	10/12/02	CIVIC
4	508456	1540932	1996	HONDA	10/15/02	ACCORD
5	510511	1541151	1994	HONDA	10/18/02	ACCORD
6	511384	1541098	1995	HONDA	10/19/02	ACCORD
7	510519	1541301	1997	HONDA	10/20/02	ACCORD
8	506034	1544827	1996	HONDA	10/23/02	ACCORD
9	511622	1542343	1994	HONDA	10/24/02	ACCORD
10	513009	1540875	1994	HONDA	10/25/02	ACCORD
11	510841	1543096	1997	HONDA	11/01/02	ACCORD
12	507674	1539989	1994	HONDA	11/04/02	ACCORD
13	503693	1540456	1994	HONDA	11/05/02	ACCORD
14	511984	1542603	1994	HONDA	11/08/02	ACCORD
15	514597	1541363	1994	HONDA	11/08/02	ACCORD
16	506053	1535721	1994	HONDA	11/08/02	ACCORD
17	511551	1540004	1995	HONDA	11/08/02	ACCORD
18	504396	1543033	1996	HONDA	11/08/02	ACCORD
19	514597	1541363	1994	HONDA	11/09/02	ACCORD
20	513492	1535572	1995	HONDA	11/15/02	ACCORD
21	513543	1540593	1997	HONDA	12/04/02	ACCORD

Table 3. A representative example of the clusters found by the algorithm.

6. CONCLUSIONS

Stolen vehicles cost victims, law enforcement, and insurance companies time and money; and it creates a threat to public safety, and even worse (!) increase everyone's insurance premiums. First, we developed an animated map that can simulate a given set of criminal activity as point stimuli on a computer spot map. Then, we developed a clustering algorithm to report events that show similar patterns (over time and space) on the map. When animated, the clustered events show hotspot-like, orderly characteristics that are very likely to be the reflections of the underlying patterns of the criminal events.

A major obstacle to the ability to perform any computer aided type of analysis is the difficulty of accessing the sufficient data in a form that can be analyzed. This data must contain all the sufficient information (data fields) required for the analysis. It should be noted that the actual time of theft of the vehicle is an estimate considering the time at which the theft was reported. In addition to the data being recorded and entered correctly, for more complex analyses, the recovery information must also be recorded and correlated with the theft information. For any type of spatial analysis, the theft and recovery address must be geocodable. This presents a tremendous challenge as the data is often recorded as intersections or without sufficient detail to allow it to be geocoded.

Each piece of information to be recorded undergoes a life cycle that may result in missing, misspelled, or misnumbered data, which creates very big problems for crime analysis applications. From the creation of the criminal data on hard-copy reports, to entering it into a records management system from these crumpled hard-copy reports, the possibility of mistype or omission of the information increases. Under certain conditions, the analyst can find out and fix these typos, such as a misspelling of a street name. The analyst can also restore the meanings of any abbreviations used in the data entry process. However, these tasks mentioned above are very time consuming and laborious. It has been understood that an expert system must be embedded in thoroughly debugged parser to be able to reach high utilization of the available data (Johnson 2002).

Therefore, as an agency plans to get started with geographic information systems (GIS), several important issues must be addressed, from the depth and purpose of the applications, to training requirements of data analysts and data-entry employees (Hughes 2000). It should also be kept in mind that the greater complexity, the greater cost.

Even though developing GIS applications can be time consuming and costly, it is worth having the ability to attain a geographical perspective of incidents within the community (Hughes 2000). GIS also eases the visualization of data, which helps law enforcement officers discover the patterns of incidents and take necessary measures to prevent them (Helms 2002; Hughes 2000).

However, it should kept in mind that small-scale GIS applications are far from efficient in monitoring criminal activity unless they are made compatible for data-sharing. The main reason is that criminals do not respect jurisdictional borders and stolen vehicles in one jurisdiction can be dropped in some other jurisdiction. Such incidents are either hard to follow because of difficulty of obtaining relevant data from other databases, or they cause duplicate efforts for the jurisdictions that are involved. Therefore, the criminal justice agencies must coordinate with other agencies to arrange for data sharing as they develop new automation systems.

Data sharing among jurisdictions have become especially important after September 11, 2001. The US Congress acknowledges that more than four months before Atta flew a jetliner into the World Trade Center, a warrant for his arrest was issued in Broward County in Florida for driving without license and failure to appear in court. Atta was stopped in a neighboring county for a traffic violation after the warrant was issued but due to the inability to share information across county lines, he escaped arrest. Today, it is collectively agreed by Florida Sheriffs that information sharing is a critical need in Florida and these efforts can serve as a national model for efficient policing.

Department of Criminal Justice and Department of Engineering Technology at the University of Central Florida have collaborated with Orange County Sheriff's Office and most of the Florida counties to eliminate duplicate efforts and create opportunities to suppress cross-jurisdictional criminal activity. In preventing auto-thefts, one must consider that a small number of known criminals are responsible for a big chunk of auto theft incidents, the police officers should be aware of bail/parole/release information on these offenders, which can be easily accomplished by data sharing.

In conclusion, our clustering analysis helps automate the task of identifying similarities among auto theft incidents to group them together. Although the automation makes the accomplishment of this laborious task easier and faster, it also brings out the question of how robust the automation is. In the previous section, we showed the validity of the clusters found by our algorithm. However, the principles behind the algorithm are fixed (static) and based on the insight the detectives we work with have given us. These principles may need to be revised our before applying our algorithm to other types of criminal events, complying with the classical understanding in Artificial Intelligence is that the expert can never be replaced by the expert system. For example, if the analyst is concerned with linking context and concentration (Kennedy *et al.* 2001), where the primary goal is to detect why crime is concentrated at the hot-spots, rather than cold-spots. Then, the drop location may lose its importance and instead the theft location may be the primary focus, which would allow the analyst find where the criminal activity is concentrated and then try to understand why these hot-spots hit schools or shopping malls.

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