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Aoristic Signatures and the Spatio-Temporal Analysis of High Volume Crime Patterns

Jerry H Ratcliffe[1]

The spatial analysis of crime and the current focus on hotspots has pushed the area of crime mapping to the fore, especially in regard to high volume offences such as vehicle theft and burglary. Hotspots also have a temporal component, yet police recorded crime databases rarely record the actual time of offence as this is seldom known. Police crime data tends, more often than not, to reflect the routine activities of the victims rather than the offence patterns of the offenders. This paper demonstrates a technique that uses police START and END crime times to generate a crime occurrence probability at any given time that can be mapped or visualized graphically. A study in the eastern suburbs of Sydney, Australia, demonstrates that crime hotspots with a geographical proximity can have distinctly different temporal patterns.

KEY WORDS: crime; policing; spatiotemporal; aoristic; temporal; GIS.

1. INTRODUCTION

When the Brantinghams described the four dimensions of crime as the legal dimension, the offender dimension, the target dimension and the importance of place, they described a place as "a discrete location in time and space at which the other three dimensions intersect and a criminal event occurs." (Brantingham and Brantingham, 1981: 8). Environmental criminologists, police analysts and geographers have all contributed significant enhancements to the spatial description of criminal incidence, and the use of geographical information systems (GIS) has become commonplace in many research and police operational environments.

Improvements in geocoding (the process of automatically finding mappable coordinates for locations) mean that many crime sites can be mapped, visualized and analyzed with a considerable degree of precision. This enables the location of one crime to be scrutinized in relation to the local environment or the relative position of other crime sites.

[1]School of Policing Studies, Charles Sturt University, NSW Police Academy, Goulburn, NSW 2580, Australia. e-mail: jratcliffe@csu.edu.au

The Brantinghams' description of a place (first paragraph) does however include the concept that a crime location also has a discrete locality in time. Many crimes do not lend themselves easily to temporal classification. The exact time of occurrence for an incident is often not known to the victim or to the police. This is because crimes are unlikely to be discovered at the time unless the victim is present at the offence (such as is usual in the case of assaults), the crime is witnessed by the police or a person willing to contact the authorities, or the crime is detected by some other means such as a time-stamped closed circuit television system (CCTV). Crimes that are affected by this lack of temporal accuracy often include burglary and vehicle theft, amongst the highest volume crime categories that the police record.

The lack of both precision in recorded crime data and a suitable methodology for its analysis appears to have left the temporal dimension of crime lagging behind while advances in crime location geocoding, mapping technology and user competence have allowed the spatial element to flourish. This need for a methodology for the temporal description of crime events where the time of incidence is indeterminate is the subject of this paper.

Temporal analysis already takes place at a number of different resolutions. Both the growth in the demand for information from the *risk society* (Ericson and Haggerty, 1997) and the new public management of police services through financial audit (Crawford, 1997) have generated an abundance of statistical data relating to recorded crime. Where once existed only annual figures aggregated to large areas, a quick search through the Internet can reveal a wealth of data for small areal units, such as police precincts, beats and local government areas, that are updated monthly or even weekly. Examples are available through the web pages of the Crime Mapping Research Center (www.ojp.usdoj.gov/cmrc). These data are usually broken down into crime types and may even be accompanied by maps, and the possibility now exists to monitor changing patterns of recorded crime over shorter periods than before.

2. DIFFICULTIES WITH TEMPORAL ANALYSIS

Much of the data available represents a "snapshot" of crime—a simple count of the number of incidents between two given dates. For example, tables are constructed to show annual counts of recorded crime for each of the states and territories of Australia, allowing easy comparison from one year to the next. As police officers in most urban parts of the world will tell you, however, the evening of New Year's Eve is not usually a quiet time for law enforcement agencies. If, for example, a group of youths decide to rearrange the decor in a public bar from 11.58 p.m. on 31 December 1998 until 12.03 a.m. on 1 January 1999—a period of only five minutes—the question arises as to which year the crime would be assigned? It is of course accepted by the author that given the high volume of crime over the course of a year the realistic impact of recording one incident either way would be negligible. Yet transpose this type of problem to a table of crimes per week or even daily and the issue increases in importance.

Most law enforcement agencies recognize that the lack of witnesses means they are unable to record the exact time of event of many crimes. Police recording methods reflect this inability to know exactly when a crime happened, because they do not document a START date and time and an END date and time.[2] These four variables describe the range of possible times that the incident occurred. The *time span* between the START and END date/times can be minimal and of only a few seconds, as is often in the case of robbery, to a period of many weeks or months if a holidaying family returns to find their home burgled. The *time span* reflects the full range of possible temporal opportunities for the offence, but rarely gives any indication of the actual time of the act nor the *duration* of the offence—how long the offence took to commit. This can range from a few moments for a bag snatch, to a number of minutes or even hours for a confident burglar. It should be noted that the duration (how long the offence took to complete) is different from the time span (the range of possible offence times recorded by the police).

Some law enforcement agencies do not record an end time and only document the start time of the crime. As this paper will go on to show, temporal analysis of some types of high volume crime using just start times may result in misleading analysis. It is to be hoped that this article provides some impetus for more thorough crime recording.

Time is an important component in the understanding of criminal occurrence. While it is known that crime follows opportunity, it does not necessarily follow that opportunities remain constant over time. Opportunities are unevenly distributed across time and space, and the availability of motivated offenders and suitable targets changes for many locations throughout the day (Brantingham and Brantingham, 1984: 361). In fact, police recorded high volume crime data tends, more often than not, to reflect the routine activities of the victims rather than the offence patterns of the offenders. Routine activities theory was formulated to better understand offender behavior (Cohen and Felson, 1979) but start and end times in police records generally reflect the times when a burglary victim left their house unoccupied, or when the owner of a stolen car left their vehicle unattended. An improved methodology for disaggregating crime records

[2]These can also be referred to as FROM and TO dates and times. However, to avoid confusion by mixing the terms, this paper will refer arbitrarily to START and END.

with long time spans would shift the emphasis of recorded crime data from reflecting victim behavior to a better understanding of what the Brantinghams have termed "aggregate criminal-spatial-behavior" (1984: 355).

Routine activities theory tells us that a crime requires a motivated offender, a suitable target and the absence of a capable guardian. Unfortunately for high volume property crime there is no shortage of either targets or offenders. The distribution of "suitable" targets is not constant though, as some properties may have extensive situational defensive mechanisms placing them beyond the realm of opportunist burglars and classing them as not "suitable". Similarly some cars may be garaged in secure locations drastically reducing their susceptibility to theft, as pointed out by Rengert in his investigation of the spatial and temporal hotspots for autocrime in Philadelphia (1997). Criminal opportunities therefore have a spatial element.

There is also a temporal characteristic to criminal opportunity. With household members at work or school during the day, the lack of a capable guardian during the day may be evident to a thief, but by the time evening has descended the opportunity to commit a burglary undetected may have passed. Conversely business districts will see an increase in informal surveillance and guardianship during the day but an increase in criminal opportunities at night. As crime follows opportunity it therefore becomes clear that opportunity to commit property crime is evenly distributed neither spatially nor temporally.

Two methodologies have emerged to cope with the problem of extended time spans when performing a temporal analysis of crime. A number of studies of repeat victimization have settled on the use of a midpoint halfway between the start date and time and the end date and time as a means of arriving at a single temporal point to assign the event (Anderson *et al.*, 1995; Morgan, in press; Ratcliffe and McCullagh, 1998b; Townsley *et al.*, 2000). This allows for a single exact moment to be allocated to an event of undetermined time and, although it arbitrarily selects one central moment from the range proffered by the time span, has been considered in the studies referred to as an acceptable compromise. A reasonable enough assertion, given the temporal resolution of most repeat victimization studies, that often work with times between offences measured in weeks. The variation between these midpoints and the start and end times is examined later in this paper in relation to shorter time frames.

2.1. Aoristic Analysis

A second, less-publicized, methodology generates a probability estimation that an event or number of events occurred within user specified temporal parameters based on the overlap between the search time frame and the time span of each incident. This process has been advanced both for temporal crime analysis (Gottlieb *et al.*, 1998) and in a spatiotemporal context (Ratcliffe and McCullagh, 1998a). Aoristic analysis,[3] an investigation that calculates the probability that an event occurred within given temporal parameters, and sums the probabilities for all events that might have occurred to produce a temporal weight in a given area (Ratcliffe, 2000), adds a spatial dimension to the temporal analysis. An aoristic analysis allows for spatially referenced objects such as geocoded crime locations to be weighted spatially according to a probability estimate. The term *aoristic*, one of the past tenses of the Greek verb *aorist*, denotes a past occurrence, with none of the limitations of other past tenses.

A number of criminal events (Fig. 1a–d) can be marked along a linear timeline, such as can be seen in Fig. 1. Each event has a beginning and ending point along the timeline, but the actual time of the crime is at an

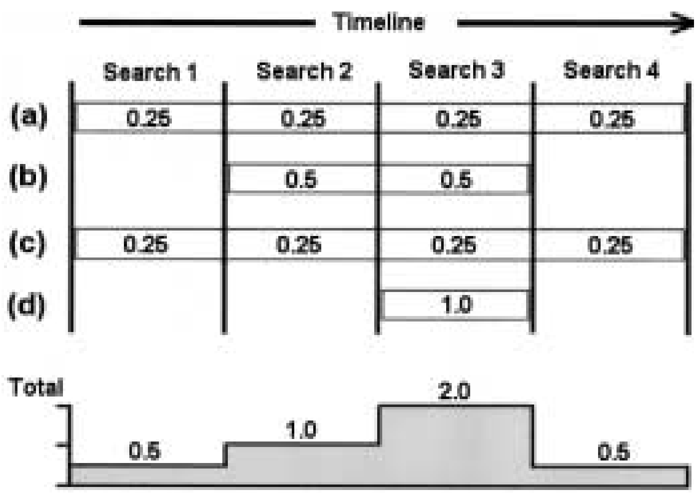

Fig. 1. Four incidents (a-d) with variable time spans indicated by the position and length of the horizontal blocks run along the timeline from left to right. The aoristic proportional weight for each search period (search 1 to search 4) is shown within the relevant block, reflecting the probability that the incident happened within that time (the appropriate length of time for a search period (1–4) is a choice for the user depending on the type of data, and could for example be one hour blocks or one day blocks). These give a total value of temporal weight as shown by the gray graph at the bottom. When the type of analysis is viewed spatially the process is termed aoristic analysis. Adapted from Ratcliffe (2000) with permission.

[3]It should be pointed out that in a broad sense an aoristic analysis is a spatiotemporal type of inquiry. However, "spatiotemporal" has a slightly different meaning in the field of geographical information science (GIS).

unknown segment of the block. The different locations of the blocks for almost every incident reflect the continuous nature of both the timeline and of the data. An aoristic temporal query examines a timeline segment and identifies those events that might have occurred then and that have a presence on the timeline at that point. An aoristic value for each incident relative to the time span it stretches across is determined by (1/time span), where the time span is expressed in search parameter units (search 1 to 4). The appropriate length of time for a search period (1–4) is a choice for the user depending on the type of data, and could for example be one hour blocks or one day blocks. Incident (d) has both a START and END time within search period 3 and therefore must have occurred in that search period. It is accordingly weighted with the maximum value of 1.0 (1/number of search blocks it spans = 1/1 = 1.0), while incident (a) covers 4 blocks and the aoristic value for incident (a) in search period 3 is only 0.25 (1/number of search blocks it spans = 1/4 = 0.25).

It is possible to total each search period and display an aoristic weight histogram (gray graph in Fig. 1). This is not a histogram of incident frequency, but a graph of the accumulated weights for the incidents in each search block, though it has some of the characteristics of a frequency distribution in that the total of all categories (the area under the graph) should equal the number of incidents included in the analysis. This is advantageous when comparing aoristic graphs as the area described by the curve gives an indication of the magnitude of the crime problem, and two aoristic graphs are comparable both for temporal trend and crime volume.

2.2. Calculating an Aoristic Value

An aoristic value (t) can be expressed as:

$$t_{is} = \Delta/(\beta_{\mathrm{i}} - \alpha_i) \tag{1}$$

where $i(\alpha, \beta)$ is a crime incident with start time (α) and end time (β), s is a temporal search parameter with start time (α) and end time (β), Δ represents a temporal unit (e.g., one minute, hour, or day), start times (α) are rounded down to unit Δ end times (β) are rounded up to unit Δ, and where $i(\alpha, \beta) \cup s$.

For example, if a crime analyst wished to understand the hourly ($\Delta =$ 1 hr) probability of a crime happening between 1100 and 1159 hr, and the first crime the analyst examined had a start time of 0915 hr and an end time of 1345 hr, the algorithm would be applied thus

$$\begin{aligned} T_{i(1100\text{–}1159)} &= 1(\Delta)/[14\ (1345 \text{ rounded up to a full hour unit}) \\ &\qquad - 9\ (0915 \text{ rounded down to a full hour unit})] \\ &= 1/(14 - 9) = 0.2 \end{aligned}$$

The analyst would then continue the same process with all other crimes that might have occurred in the hour before midday. Greater degrees of temporal resolution (i.e., minutes instead of hours) will necessitate an increase in the complexity of the outcome, but it is assumed that software would be written to automate the task.

3. THE CURRENT STUDY

The previous studies into aoristic analysis outlined the conceptual framework but did not examine the consequence of this type of study on different crime types. This issue will be developed in the following sections utilizing source data drawn from the recorded crime records held on the Computerized Operational Policing System (COPS) of the New South Wales Police Service (Australia). The state of New South Wales (NSW) has an area roughly the size of Texas (Fig. 2) with a population of approximately 6 million, policed by just over 13,000 sworn officers. The majority of the population and the officers are located in the urban conurbation of the state capital, Sydney. Data are taken from the 11 Local Area Commands (LACs) shown in Fig. 2, a mix of higher crime inner-city suburbs and larger rural regions with sparse populations.

It should be noted that criminal opportunities may vary by time of day between rural and urban areas. The data are combined here to examine the cumulative affect of a temporal analysis but a later study in this paper focuses on one (urban) police LAC as a more common application of the process.

Due to the availability of data from the NSW Police Service, the source data are drawn from a three-month download of recorded crime from each of the 11 LACs, at varying three-month blocks between October 1998 and March 2000 depending on the Local Area Command (LAC). The data from different LACs were combined to create a single crime type category.

Nine crime types have been used in this study. These categories are the main source of emphasis during the Operations and Crime Review (OCR) meetings held on a regular basis between the executive of the NSW Police Service and their Local Area Commanders, meetings that are modeled on the CompStat process. Table I shows the nine crime categories examined in this study with the numbers of incidents that have been drawn from the 11 study regions. Break and enters (burglaries) have been studied as two distinct groups: residential and non-residential (schools, commercial premises, churches, etc.). Their combined values are also shown for completeness. The table also shows the percentage of incidents in each category that have time spans of up to 4, 8, 12, and 24 hr. Only malicious damage and break and enters have greater than 20% of incidents with time spans of more than

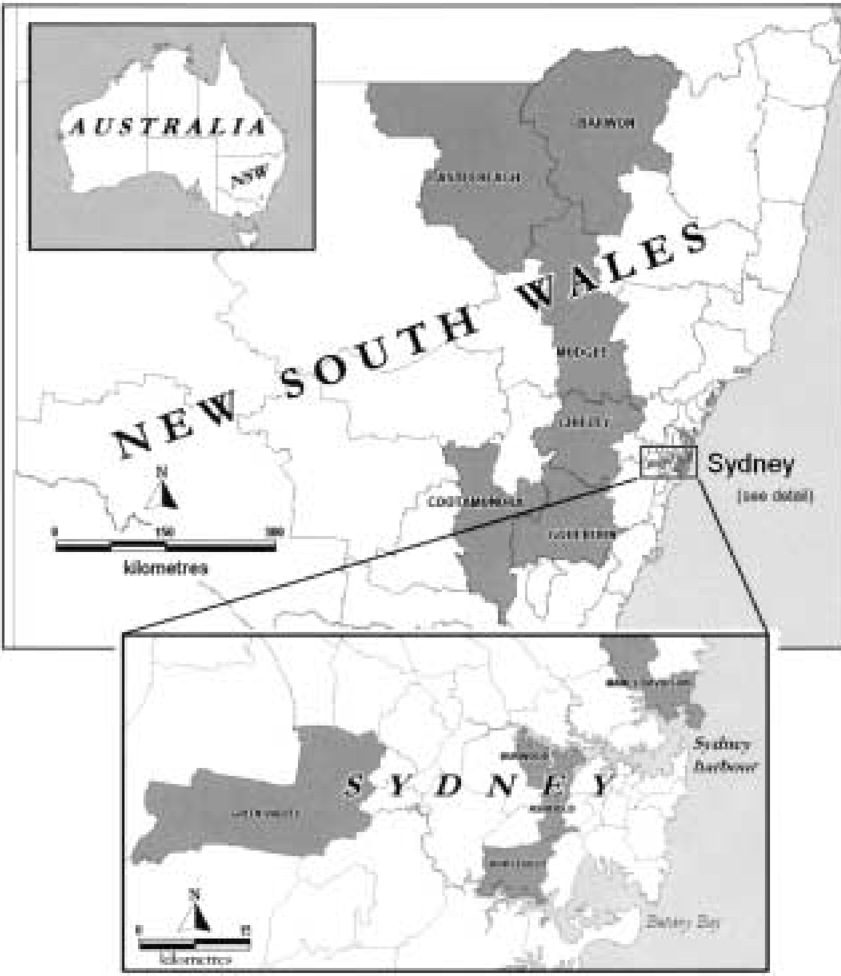

Fig. 2. The 11 rural and inner city areas where data are drawn from are shown shaded in gray. 5 are smaller more densely populated areas within Sydney, and 6 are rural, sparsely populated regions.

24 hr. Crimes that are more likely to be witnessed or experienced by the victim (robbery, assault, street offences) have over 95% of incidents with time spans of less than 4 hr, and 90% are less than 2 hr. Drugs is a more distinct category in that many incidents are police-initiated and the reports are due to arrests by the police (with a known time of arrest) and not reports from the public.

Table I. The Total of Each of the Nine Crime Categories Examined is Shown, with the Percentage of Events that had Time Spans of up to 4, 8, 12, and 24 hr[a]

	Total	4 hr	8 hr	12 hr	24 hr
Assaults	711	96.2	97.6	98.3	98.7
Break and enter (non-residential)	1859	29.4	36.5	48.0	74.8
Break and enter (residential)	3711	33.9	51.9	68.0	80.1
(Break and enter total)	(5570)	(32.4)	(46.8)	(61.3)	(78.3)
Drugs	140	92.9	94.3	95.7	97.9
Malicious damage	884	36.4	45.0	59.5	77.8
Motor vehicle crime	2193	47.3	61.9	78.9	95.6
Robbery	277	97.1	98.6	98.9	98.9
Stealing	5358	63.8	72.4	81.4	92.3
Street offences	141	98.6	98.6	98.6	99.3

[a]Residential and non-residential break and enters are regarded in this study as distinct categories and their combined values are shown in this table for completeness.

4. ANALYSIS

There are four temporal values that will be examined in this section. Each crime incident has a start and an end date/time, and from this can be calculated an aoristic value and a midpoint. For some offences, such as where an officer makes an arrest for a drugs related offence, the exact time of the incident is known and in these cases the end and start date/times are the same. The choice of temporal scale is also a factor in the analysis. Fig. 1 uses four equal-sized search periods to generate a proportional smoothing effect across the data. As the two incidents with the longest time spans (a and c) spread across four search periods the aoristic value for any period was 0.25 per incident. This search period dictates the resolution of the analysis and therefore the level of smoothing, in much the same manner as a moving average. In the search for a satisfactory medium between practical application and excessive calculation, a temporal scale of one hour was chosen for this analysis. Given the time span of most crimes (from Table I) any attempt to model changing crime patterns of less than one hour would probably be spurious (although easily possible). Longer resolutions may serve to aggregate the data too much and conceal temporal variations.

The aoristic value, midpoint, start and end times were calculated on an hourly basis for a 24 hr period for all nine crime types. An example from the NSW data for malicious damage (Fig. 3) shows there is an obvious peak in the START data between 5 p.m. and 7 p.m., matched with a similarly high peak in the END data between 6 a.m. and 8 a.m. It is likely that this is due to the high number of malicious damage reports being made to the police by business owners that close their premises in the evening and return in the morning to find damage to the property. These factors would explain

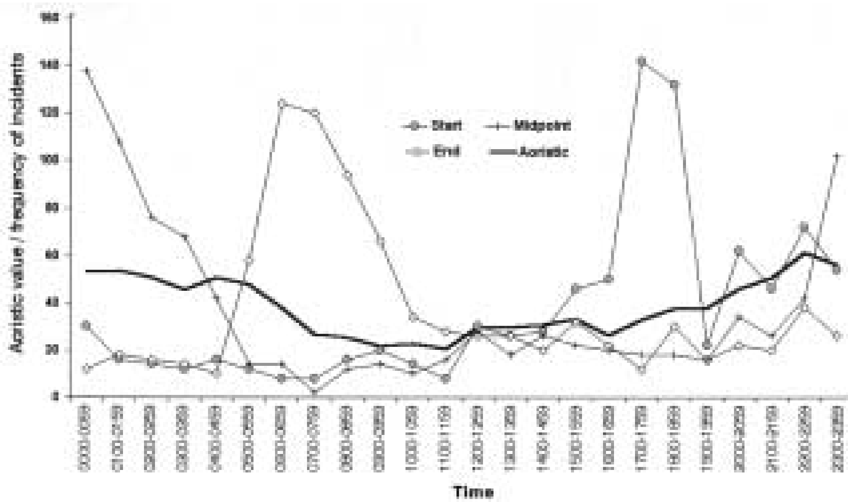

Fig. 3. Accumulated probability histogram showing four different temporal measures applied to the malicious damage data set. Start and end lines simply show the distribution of the start and end times, the midpoint is calculated from the mean of the start and end date/times, and the aoristic value is determined from an aoristic calculation, based on the time span of each incident (rounded to whole hours) where the value does not exceed 1.0 for each incident.

the high peak around midnight in the MIDPOINT set. The aoristic analysis can help to smooth incongruities in the data set, such as the influence of business opening and closing times and provides a more stable arrangement of possible criminal behavior that does not rely on arbitrary choices of possible crime time.

A correlation analysis was performed to examine the differences between the hourly changes in value between the four different measures of crime time (Start, End, Midpoint, Aoristic). This was conducted for each crime type using a Spearman Rank Correlation test. This statistical test has both strengths and weaknesses for this type of analysis. The test is able to determine if high values in one data set are matched by high values in the comparison set, and to what degree, but the necessity to rank the data (while retaining the order of high and low values) removes the magnitude of any discrepancies between the sets. The use of a non-parametric test was preferred in these circumstances where no assumptions could be made about the distribution. Spatial and temporal crime distributions are rarely, if ever, normally distributed due to the non-random nature of aggregate criminal behavior. Table II shows the correlation coefficients of the Spearman Rank test between each temporal measure across each crime type.

Table II. Correlation Coefficients for Each Crime Type

Crime	Aoristic and start	Aoristic and end	Aoristic and midpoint	Start and end	Start and midpoint	Midpoint and end
Assault	0.978**	0.951**	0.982**	0.912**	0.960**	0.947**
Break and enter (non-residential)	–0.114	–0.040	0.810**	–0.525	–0.017	–0.158
Break and enter (residential)	0.490*	0.714**	0.702**	0.653**	0.047	0.216
Criminal damage	0.247	–0.439	0.749**	–0.215	0.403	–0.672
Drugs	0.918**	0.922**	0.930**	0.806**	0.857**	0.838**
Motor vehicle crime	0.700**	0.011	0.534*	0.586*	–0.074	–0.617
Robbery	0.985**	0.949**	0.977**	0.922**	0.952**	0.946**
Stealing	0.888**	0.784**	0.820**	0.828**	0.590*	0.489*
Street offences	0.988**	0.966**	0.992**	0.956**	0.995**	0.959**

*Indicates a significant positive correlation at the 0.01 level.
**Indicates a significant positive correlation at the 0.001 level.

From Table II it can be seen that two categories of crime type emerge. There is a significant correlation between all of the temporal measures of the assault, drugs, robbery, stealing and street offences data sets. All of these offence types had greater than 60% of their total events with time spans of less than 4 hr (Table I, column 3) and if stealing is removed from the set the percentage of events with a 4 hr or less time span rises to over 90% for each category. This suggests that because the majority of offences in this category have short time spans and the time of the incident occurrence can be more easily determined or estimated, any of the four temporal measures will generate the same trend in high or low values. NSW is not a region with endemic crime rates, and the sample data sets used in this study are not large in some categories (Table I, column 2). Still, these results may be helpful to researchers and police analysts who may worry that a drugs, robbery, or street offences trend drawn from only the start or midpoint of a crime data set may be erroneous.

The lack of correlation for the other offence types suggest that start and end date/times are not effective measures of any temporal trends in these crimes (break and enter, vehicle crime, malicious damage). They may, as in the case of break and enters, be a better indication of the routine activities of the victims. The relationship between the aoristic and the midpoint data sets remains significant with a 99% confidence. This may at first hand appear strange, given that neither the start nor the end measures had a significant positive correlation with the aoristic data set. However the midpoint value for each hour block is a summation of the arithmetic means ([end − start]/2) that fall within the one hour block and the aoristic value is a summation of a probabilistic distribution that will generate central values if the start and end date/times from which it originates are at extremes. This causes the aoristic set to tend towards a centralized distribution rather in the same way that central limits theorem dictates that the means of samples drawn from *any* distribution will tend themselves to be normally distributed (Davis, 1986: 51). This can be seen in Fig. 3 where the effect of notable peaks in the start and end times generates a high peak in the midpoint set in the hour after midnight.

The aoristic value for each block between the start and end peaks contains a value of [1/time span] and due to the location of the start and end peaks this generates an increase in values that follows the same trend as the midpoint, but not of the same magnitude. One of the limitations of the Spearman Rank Correlation is the inability of ordinal data to reflect this distinction between trend and magnitude.

4.1. Magnitude

To assess the impact of magnitude as a measure of any difference between the midpoint and the aoristic value, a second analysis was performed. This analysis was designed to see if the significant correlation in the trends of the midpoint and aoristic data sets was matched by a similar goodness of fit from the two sets. A two sample (aoristic and midpoint) χ^2 test statistic was calculated for each crime category for each of 24 hr. The use of a χ^2 test allows for a non-parametric examination of the difference between an observed frequency distribution (midpoint values) and a theoretical distribution (aoristic set). The results are shown in Table III.

The crime data sets that have the highest Spearman Rank Correlations show a similarly close goodness of fit. The noticeable difference is the stealing data set. Although any temporal measure (start, end, midpoint, aoristic)

Table III. Chi Square Value and Significance for Two Sample Test with Aoristic and Midpoint Sets

	χ^2 (Aoristic and midpoint)
Assault	2.17
Break and enter (non-residential)	310.15[a]
Break and enter (residential)	347.65[a]
Criminal damage	181.43[a]
Drugs	7.05
Motor vehicle crime	174.26[a]
Robbery	1.44
Stealing	194.64[a]
Street offences	1.215

[a] Indicates a rejection of the null hypothesis and a significant difference between the sets at the 0.01 and 0.001 levels ($df = 23$).

correlates with any other and has a similar trend, the midpoint and aoristic sets have a significantly different distribution of values and there is a significant difference between the sets ($\alpha = 0.001$) when actual values and not rankings are compared. The results for break and enter, vehicle crime, and malicious damage all show a clear pattern. Although the trends of the midpoint and aoristic values are similar (Table II, column 4) the accumulation of differences between corresponding values is significant. The results suggest that for these types of crime the use of a midpoint is only acceptable for the creation of a general trend where the magnitude is not relevant. The magnitude of the differences between the sets is significant enough that if an actual measure of hourly differences is sought, the use of a midpoint may give an inaccurate indication of relative values and a probabilistically-weighted value such as an aoristic measurement may be more appropriate.

5. VISUALIZING AORISTIC VALUES

Visualization of the result can be either as a static image or group of images, or as an animation. An example static image is shown in Fig. 4 where the location of all motor vehicle crimes (including theft from and theft of vehicle, but not including traffic violations) in two LACs of Eastern Sydney (Eastern beaches and Eastern suburbs) are mapped for the time between 6 p.m. and 6.59 p.m. Three month's worth of data are shown. Each location is weighted according to its aoristic value, ranging from just above 0 for crimes with long time spans (low weighting, light shade), to exactly 1.0 (highest weighting, dark shade) for those crimes that were known to be committed within this one hour period.

Ratcliffe (2000) describes the adaptation of a kernel smoothing equation to provide a temporally weighted surface algorithm that can generate isometric surfaces that are sensitive to aoristically weighted values. An aoristic weighting standardizes each crime location such that the total of all weights for all possible times at a single point equals 1. In a formal form this means that for all points (n) in the study area the temporal weight (t) of a point (i) at a snapshot search time (q) can be defined as

$$\sum_{1}^{n}\sum_{1}^{q} t_i = n \qquad \text{where} \sum_{1}^{q} t_i = 1 \tag{2}$$

If this standardization is applied to a smoothing algorithm (here using a quartic kernel algorithm, but in reality most kernel smoothing processes will work in a similar manner) then the addition of the aoristic value (t_i) in the range (>0 to 1) serves to generate a temporally weighted intensity

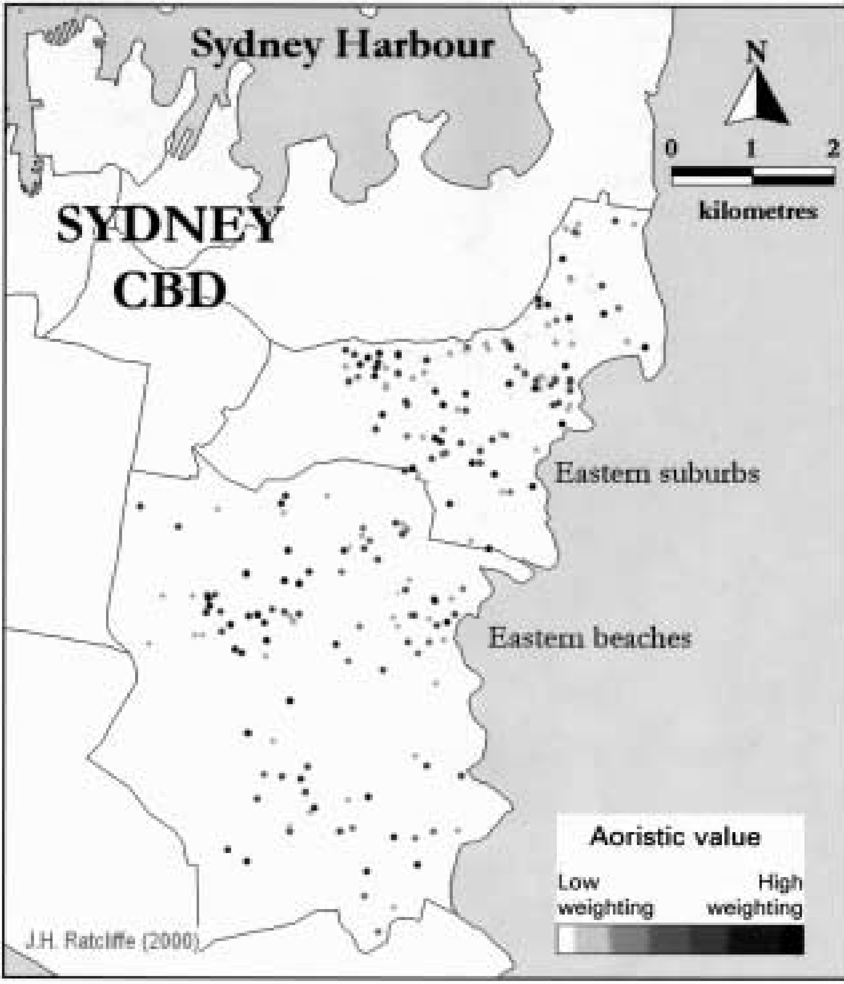

Fig. 4. Aoristic values of all vehicle crimes that could have occurred in the period from 1800 to 1959 hr, drawn from a three-month dataset for 2 LACs in east Sydney.

surface

$$\hat{\lambda}_\tau(s) = \sum_{d_i \leq \tau} t_i \frac{3}{\pi\tau^2}\left(1 - \frac{d_i^2}{\tau^2}\right)^2 \tag{3}$$

where s represents the center of the search circle, τ the bandwidth, and d is the distance of each point (i) within the bandwidth (τ) from the center of the search area (s). The calculation of the intensity $\lambda_\tau(s)$ is therefore the summation of the intensity of those values that have a smaller distance from *s* than *d*.

The smoothing operation was performed using Hotspot Detective (www.bigfoot.com/~hotspot.detective), though a number of proprietary GIS programs (such as ArcView and MapInfo) have smoothing software in various forms. The result, when applied to the data shown in Fig. 4 can be seen in the surface generated in Fig. 5. A smoothed surface has aggregated

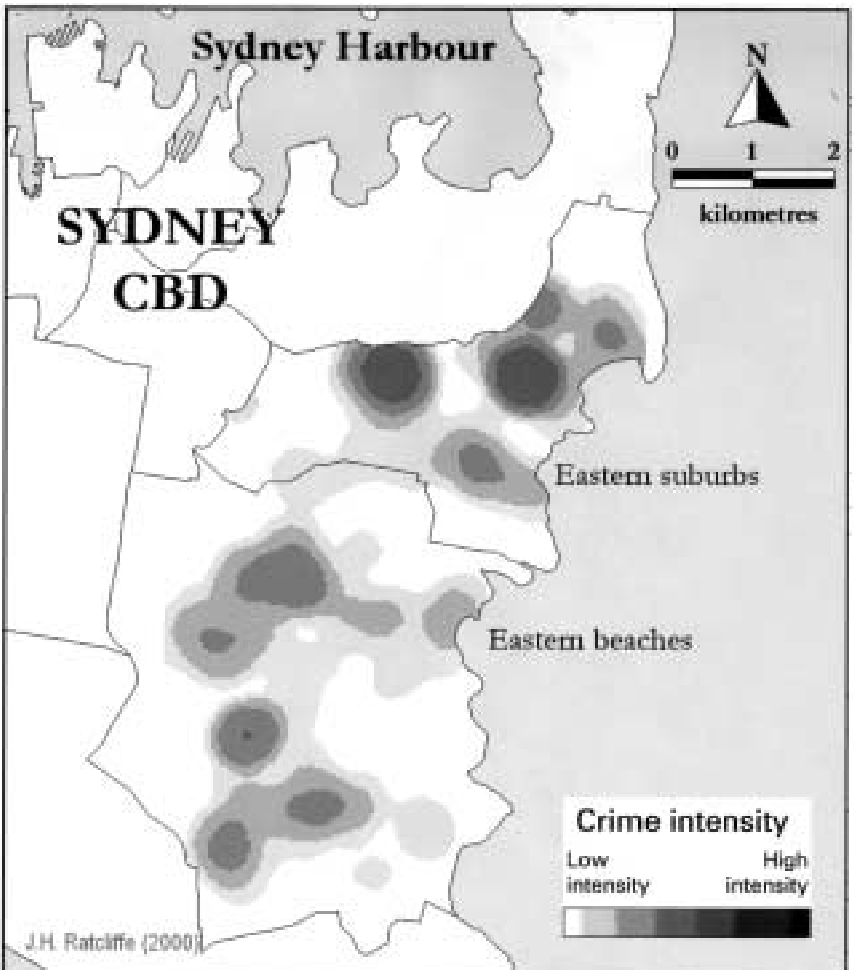

Fig. 5. Hotspot surface for eastern Sydney vehicle crime between 1800 and 1859 hr. Kernel surface of points from Fig. 4 weighted by aoristic value with a grid size of 40 meters and a bandwidth of 500 meters.

the 176 possible events that may have occurred within the search parameters into an isometric, aoristic surface. By inclusion of the aoristic value in the algorithm, the resulting surface has both a spatial constituent, and a temporal component that is more sensitive than the result of an SQL query.

Animation techniques have been used for some time now to display the temporal characteristics of spatial data (Fisher, 1994; MacEachren, 1994, Petersen, 1995). Animations of changing weekly crime patterns are now available on the Internet (examples can be found through the pages of the Crime Mapping Research Center—www.ojp.usdoj.gov/cmrc). The primary method of generating these animations is to create a number of snapshot maps, similar to Fig. 5, and then run them through an animation package (of which there are a number available for free from the Internet). The medium of this article does not permit the inclusion of a demonstration, but readers are invited to view a 172 Kb animation of hourly changing break and enters patterns in East Sydney (the area shown in Fig. 4 and Fig. 5), drawn from over 2000 incidents, at http://www.csu.edu.au/faculty/arts/policing/research/ratcliffe.zip

Although the addition of a temporal component to a kernel smoothing equation (described above) is an enhancement to the process, there are still limitations to the value of kernel estimation. These include the appropriate choice of bandwidth, cutoff values (McLafferty *et al*., 2000: 82) and the choice of class limits (color bands) for the graphical display. A potentially clearer method is to reclassify the map into a simpler display of two types of crime hotspot area; "hot" or "not." The next section of the paper demonstrates a spatiotemporal application.

5.1. Aoristic Signatures

An alternative method of display for the temporal characteristics of crime hotspots is to combine a crime hotspot map with a graphical display of aoristic temporal distribution. An aoristic signature is a chart (line or bar are both suitable) that shows the aoristic values across a complete range of study times for a crime hotspot. This temporal "signature" is attached to the crime hotspot either graphically (as shown below) or as a separate display. It can also be shown in tabular form but a graphical display is clearer. These study times may be shown in a variety of temporal scales such as one hour blocks within a 24 hr period (as shown below) or in days of the week.

The first stage is to reclassify a map of crime into a binary surface or "hotspot" and "not-hotspot". While this can be done using "Spatial" and Temporal Analysis of Crime" (STAC), a software package commonly used in the U.S. law enforcement domain, there are a number of theoretical problems with the underlying process of the software. The end result displays crime hotspots as standard deviational ellipses, shapes that take no account of the spread of points around the mean center in different directions (Ebdon, 1996: 136). Also the STAC-generated shapes rarely mimic either the morphology of the points used in the analysis or the underlying geography of the human environment.

To demonstrate an alternative method to STAC, a binary (hot/not hot) crime intensity surface was generated using a two-stage process involving a class of statistic termed Local Indicators of Spatial Association (LISA) outlined in Ratcliffe and McCullagh (1999: 387). Employing the same study area of the Eastern Suburbs of Sydney (from Fig. 5), we can see first the distribution of all vehicle crime locations in the two police Local Area Commands for a six-month period (Fig. 6). The use of graduated circles in Fig. 6 helps to show the volume of crime more clearly when a number of offences occur at the same location, however it does not clearly delineate areas of higher than usual criminal activity. The use of LISA statistics can do this, as is shown in Fig. 7.

The two-stage process creates a binary surface with 9 separate vehicle crime hotspot regions that have a shape that follow the geography of the crime points, and have a definite boundary (gray areas in Fig. 7). The individual crime sites within these hotspot regions can be isolated and analyzed hotspot by hotspot for their aoristic temporal signatures. The signature bar graphs that accompany each crime hotspot in Fig. 7 show the aoristic probability distribution of the crime events for each area, running in hourly blocks, from a first block of 0000–0059 through to 2300–2359 at the far right. In this manner the aoristic pattern of each hotspot can be visualized. These aoristic signatures are useful in that they clearly show the aoristic temporal pattern of each crime hotspot, without the need for animation techniques or pages of tables. A relatively simple graphical display is sufficient to demonstrate the changes in event probability over time in a manner that is easy to explain to non-technical audiences.

It is clear from Fig. 7 that although a number of crime hotspots are close to each other, they display different aoristic signatures and volumes. While the changes in volume are understandable, the differences in aoristic signatures for hotspots 1 and 2 are interesting in that the times for the highest probability of vehicle crime are markedly different even though the two sites are only about one kilometer apart.

6. CONCLUSIONS

One of the key aspects of intelligence-led policing is the provision of timely intelligence to operational officers, but "an intelligence structure

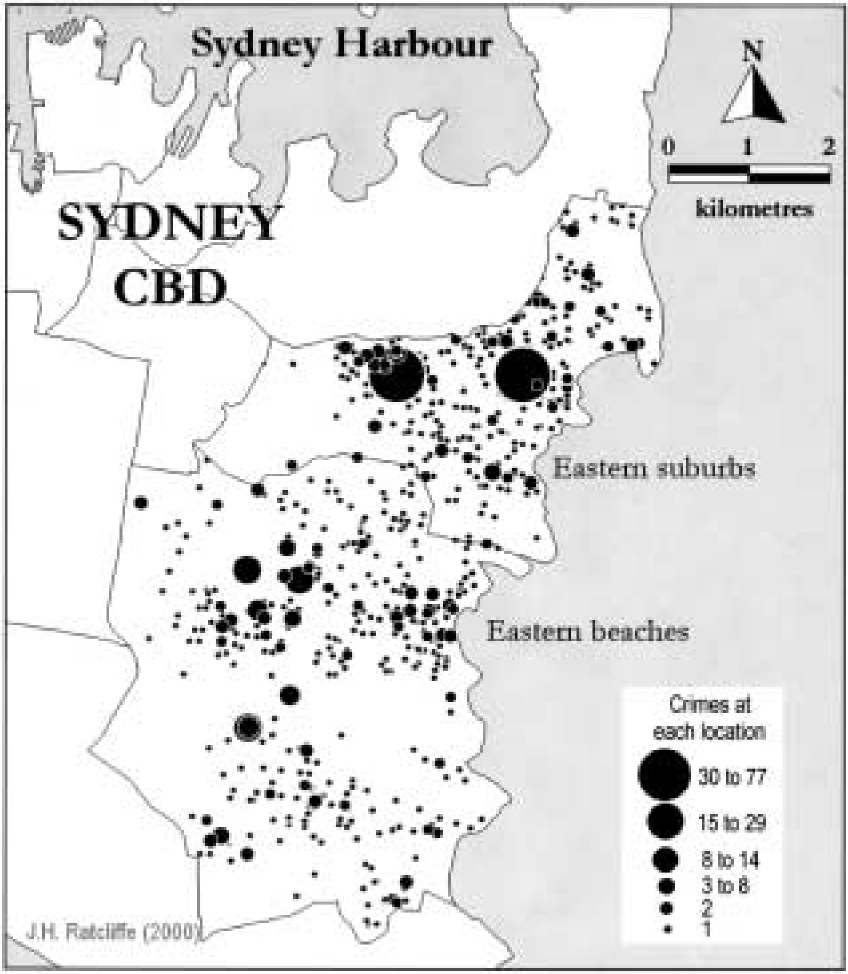

Fig. 6. All 1100 vehicle crime locations for the eastern Suburbs of Sydney for a six-month period. The number of offences at each location are shown by graduated circle sizes.

without effective analytical capability will simply be unable to give an accurate overall picture of crime and criminality'' (HMIC, 1997: 4). The advancements in GIS are pushing crime mapping to the fore and this is one of the real growth areas in modern police crime analysis. The reality however is that crime hotspots have a temporal component that is rarely explored in a police operational environment. They are not constantly active with criminals over a 24-hr period, and the level of criminality in the area

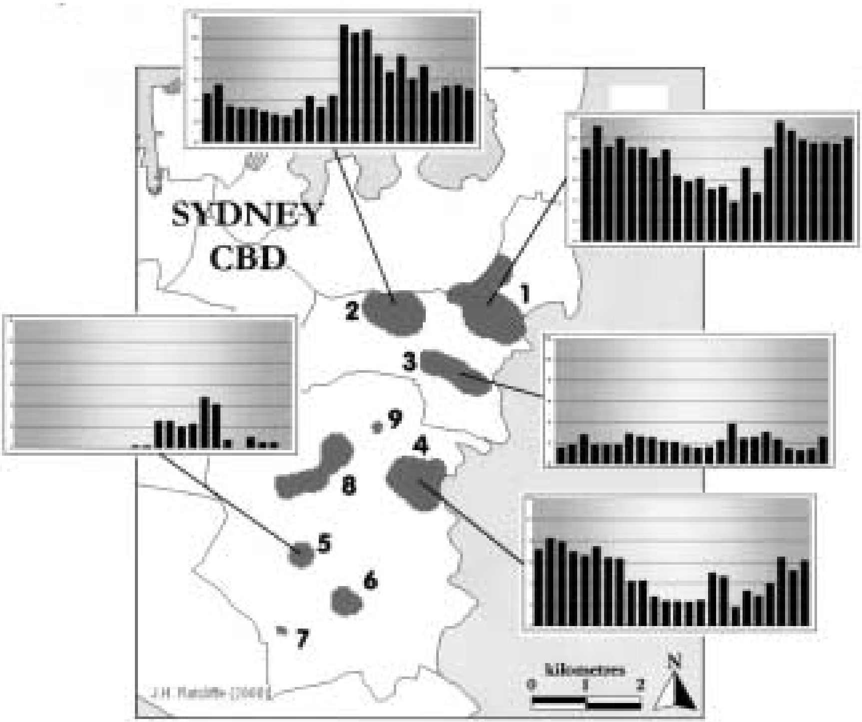

Fig. 7. Nine hotspot areas identified through the use of LISA statistics. Of these nine regions, the aoristic signatures of five are shown as hourly bar graphs running from 0000–0059 to 2300–2359. Hotspot regions 1 and 2 are only a few hundred meters apart but display markedly different aoristic temporal crime distributions for vehicle crime. Region 5 is centered on a retail park that only experiences vehicle crime in the afternoon and early evenings.

of hotspots waxes and wanes over a number of different temporal scales. Strategic analysts may find a map of crime sufficient to identify areas for further examination, but operational and tactical analysts may need to extract more information to maximize their intelligence product. An aoristic signature will give a better indication of aggregate criminal-spatiotemporal-behavior than recorded crime data alone. Furthermore the environmental criminologist seeking a deeper understanding of criminality in a region may find that an aoristic signature unlocks another dimension to the spatial dynamic. Crime mapping is one tool in the arsenal of the crime analyst, a weapon that may be enhanced with other tools such as aoristic analysis and the plotting of aoristic signatures.

The statistical difference between the use of midpoint and aoristic data at the hour level for high volume crimes does question the validity of hourly temporal patterns extracted by more conventional means. The statistical importance of different temporal resolutions (such as 30 minute intervals, 2 hourly, 4 hourly) is another question that begs an answer in the near future.

In the particular example used in this paper the significance of sub-area variation (Tilley *et al.*, 1999: 17) is demonstrated by the aoristic variation between two proximate crime hotspots in the Eastern suburbs of Sydney, where a different policing response in terms of shift rotas alone might prove fruitful. While the software does not yet exist to easily generate aoristic signatures for crime hotspots, this is undoubtedly an enhancement to GIS capability that would be of benefit to police tactical and operational planning. An aoristic analysis can go some way to extracting this temporal variation between crime hotspots and hopefully provide some of the practical application so often sought from the academic field by practitioners.

Aoristic signatures cannot tell us the hunting patterns of individual offenders. The start and end times of incidents are a better indication of the behavior of victims and their routine activity than a signal of offender movement. But by better understanding the routine activities of victims we can get a clearer view of not just their personal victimization liability, but also a better idea of the criminal opportunities associated with the property they leave unguarded.

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