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Research Article

Aoristic analysis: the spatial interpretation of unspecific temporal events

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Abstract. Temporal limitations of GIS databases are never more apparent than when the time of a change to any spatial object is unknown. This paper examines an unusual type of spatiotemporal imprecision where an event occurs at a known location but at an unknown time. Aoristic analysis can provide a temporal weight and give an indication of the probability that the event occurred within a defined period. Visualisation of temporal weights can be enhanced by modifications to existing surface generation algorithms and a temporal intensity surface can be created. An example from burglaries in Central Nottingham (UK) shows that aoristic analysis can smooth irregularities arising from poor database interrogation, and provide an alternative conceptualisation of space and time that is both comprehensible and meaningful.

1. Introduction

Recognition of the importance of time within many GIS has brought with it a recognition of the limitations of many GIS to cope with this extra variable. There now exists a considerable literature on spatiotemporal databases and their design (Al-Taha *et al.* 1994) and this is perhaps in response to the criticism levelled at some GIS that the database is often perceived to be one of the weaker aspects of the system. For example, advances in spatial display and analysis have not been matched by improvements in database functionality, and 'the rigid spatio-temporal framework embedded in the current generation of GIS is too restrictive to capture the current urban reality' (Sui 1998, p. 661).

Temporal variables relating to spatial objects are stored in the database. Previously; 'the conceptual and practical difficulties in representing and analysing complex spatial patterns within GIS have caused the representation and analysis of the temporal dynamics of those spatial patterns to be ignored' (Peuquet 1994, p. 442). With limited analytical capability within the GIS database, often accompanied by the assumption that changes occur at known times with a fixed duration, the opportunities to examine the changing spatial distributions and patterns of objects over time are limited. The picture is more complicated when the times of changes are unknown or have variable time spans and it is only possible to estimate a probability that a change occurred at a given time.

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While much of the previous published work has examined the problems associated with modelling the geographical change in one variable over time (Langran 1989, Langran 1993, Lowell 1994, Raafat *et al.* 1994, Peuquet and Niu 1995), this paper examines the difficulties in visualising the change over time of a number of objects that are fixed geographically, but have varying and often unspecific temporal patterns.

The paper builds on previous work in this area (Ratcliffe and McCullagh 1998) by developing the concept of accurate selection and weighting from the temporal data structure, and then proceeds to suggest a method of displaying the spatial output from a probabilistically weighted temporal query. Although this method of examining indeterminant temporal events has been hinted at before (Gottlieb *et al.* 1998) it has not been developed in any spatial context. As the problem is divided into two components (a temporal selection issue and the generation of a temporal surface) the paper begins by reviewing and enhancing the temporal selection aspect.

2. Aoristic analysis revisited

Events that have an unknown time of occurrence present a degree of analytical difficulty, and query facilities in current databases often struggle to cope with the subtleties of the problem. A simple example to demonstrate the problem could be of an event such as a festival that takes place from 29 June to 2 July. If we wished to know how many festivals occurred in each month of the year, where would our example festival be counted? In this case an average of the start and end time to fix a single date would still leave some ambiguity, or it might be considered at first glance reasonable to accept a selection based on either the start or end date. This latter option becomes more difficult if a second festival lasts for over a month. With a time span of 35 days from 29 June to 2 August, it appears unreasonable to catalogue the event in either June or August (start or end date). A more rigid query designed to extract every record that only happened definitely in one month (for example July) would ignore both festivals as falling outside the search parameters.

Aoristic analysis does not exclude any temporal possibilities and selects every object from the database that might have occurred within the search parameters. Aoristic analysis is an investigation that calculates the probability that an event occurred at a location within given temporal parameters and assigns this temporal probability weight to the spatial object, given that the actual instance of the event is indeterminate but occurred between two known times. It is possible to sum the probabilities for all events that might have occurred within a given study area to produce an accumulated temporal weight for that region. With an aoristic analysis the second festival in our example would be selected in a search of June, July and August.

Examples from previous work in this area have come from the field of crime analysis (Ratcliffe and McCullagh 1998) though other researchers have developed their own conceptual framework for analysing temporal dimensions of a specific problem. An example of this is the approach to wildfire modelling of Yuan (1997). With regard to crime analysis, there are a number of categories of crime where the exact time that the incident occurred is unknown. Burglary and vehicle crime are among the most common types of crime in Western societies and can rarely be pinpointed with great accuracy in a temporal sense. A person might leave their car overnight or to go shopping and return to discover the radio stolen, and a family might go on holiday to return to a burglary scene. Objective interpretation of the last time they were at the property (referred to here as the START date/time, but can be also be referred to as the FROM date/time) and the time they returned (referred to here as the END date/time, but can be also be referred to as the TO date/time) can not permit an intuitive guess as to any possible event time. All that is available is an event time span, extending from the START date/time to the END date/time. Henceforth the definition of time span does not express the length of time the incident took to happen, but is defined as the extent or range of possible times within which the incident occurred.

A temporal query can use aoristic analysis to extract all possible events from the database and assign a probability weighting to each event within a defined search parameter. The probability weight reflects the possibility that the actual incident happened within that time slice of the overall event time span. The model requires the search criteria to be of equal duration, or if different temporal search criteria are required, a different choice of weighting based on the smallest search time slice.

A timeline can be thought of as linear and unidirectional, each event beginning at a fixed marker along the line and ending at another fixed marker. The different locations of the markers for almost every incident reflect the continuous nature of both the timeline and of the data. An aoristic temporal query interrogates a slice of the timeline and identifies those incidents that have a presence on the timeline at that point. This is shown in figure 1 where the horizontal axis displays the timeline along which four events (*a–d*) are displayed, some being longer (*a* and *c*) than others (*b* and *d*). Each incident has a known time span (indicated by the length of the blocks) with a known start point (START date/time) and end point (END date/time). Incidents with longer time spans are less likely to have occurred within specific search blocks (searches 1–4) and are therefore weighted accordingly (1/number of search blocks). Incident (*d*) has 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 = 1/1 = 1.0).

It is possible to total each search period and display a temporal weight histogram (grey graph in figure 1). It should be made clear that this is not a histogram of incident frequency, but a graph of the accumulated weights for the incidents in each search period. This provides a different conceptual approach to temporal data, an

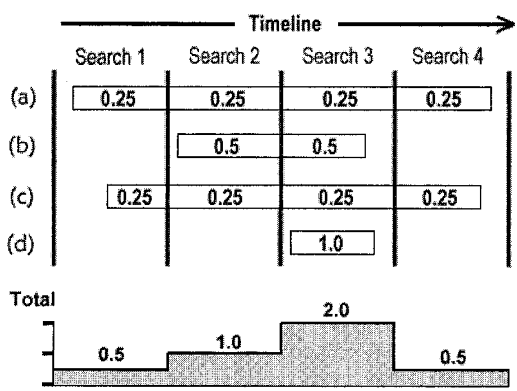

Figure 1. Aoristic analysis. Four incidents (*a–d*) with varying time spans indicated by the position and length of the horizontal blocks run along the timeline from left to right. Each search period (1–4) calculates the probability that an incident happened within the period and allocates a weight accordingly. These give a total value of temporal weight as shown by the grey graph at the bottom.

approach that often provides a better indication of the probable temporal distribution of events. This can be seen in figure 2 where four different temporal search techniques are applied to non-residential burglary data from Central Nottingham (UK) for the period April 1995 to April 1997. The data was extracted from the Crime Recording System of Nottinghamshire Police and comprises 2524 separate incidents relating to all burglaries that did not occur at dwelling premises. Like most city centres, the centre of Nottingham is dominated by businesses that open in the morning and close in the evening, with many of the burglaries happening overnight. This is evident from figure 2 where it can be seen that a temporal search based on the START time suggests a massive peak between 6 pm and 7 pm when the employees go home and leave the premises unattended. Temporal queries based on the END time show high values between 8 am and 10 am as the employees return to work and find a burglary has taken place. Taking an average of the START and END times generates a peak at another time (between 1 am and 3 am). An aoristic search (shown by the solid line in figure 2) works to smooth the result and indicates that there is a rise in the accumulated temporal weight of incidents (total aoristic value) in the early hours of the morning. The level drops off throughout the day when people are in the shops, only to rise again once the locations are left unattended in the evening. This type of analysis seems intuitively more reasonable and considers a measure of the probability of event occurrence instead of reflecting the work patterns of employees and adding emphasis to specific times with no statistical or logical reason.

Among the advantages of aoristic analysis is the ability of the process to smooth irregularities in the temporal data set and reduce the impact of incongruities such as the business opening and closing times demonstrated in figure 2. Spreading the probability of each event occurrence across the full spectrum of possible hours or days presents a more realistic interpretation of the likely pattern of total events. With a proportional weight attributed to each event, the total weight for each

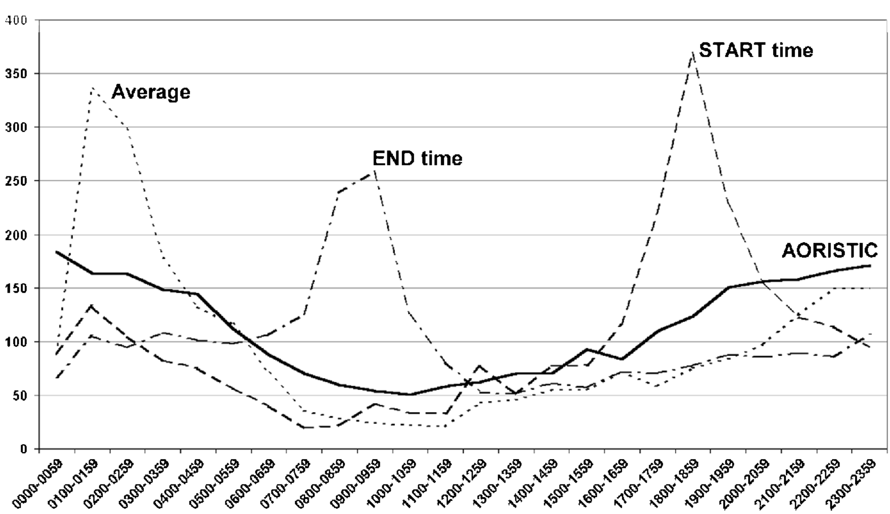

Figure 2. Accumulated temporal weights histogram showing four different temporal search techniques applied to non-residential burglaries in Central Nottingham (April 1995 to April 1997). Aoristic analysis can help to smooth incongruities in the data set, such as the undue influence of business opening and closing times.

incident is the same and the area under the curve of each search technique is the same (figure 2). The total weighting is the same irrespective of the actual time span of the incident.

The process is limited in that the search period for a number of different searches must be of the same duration. This notion of duration is similar to a spatial resolution in that smaller temporal resolutions give greater accuracy at the expense of processing time. It would be possible to display a temporal histogram (such as the one in figure 2) for every minute or even second in a 24 hour period, though for non-residential burglary the considerable increase in processing would probably not generate a proportionately improved output.

3. Visualising temporal probability

With the use of aoristic analysis to determine a temporal weight for each spatial object, the weighting can be displayed as a cartographic variable. Careful calculation of the weight is necessary in certain cases. In our example of non-residential burglaries in Central Nottingham, the desire to better understand the hourly pattern of crime is complicated by those incidents that have time spans in excess of 24 hours. Figure 3 shows the temporal frequency of the example data. An event with a time span of 48 hours will have a weighting of 0.02083 (1/48) for each hour, but will feature in each hourly band of the histogram twice. Each hour long block of search time will therefore carry a weight of 0.041667 (2/48). Figure 3 shows a noticeable peak in the period from 11 to 15 hours, approximately the time between many store and business closing and reopening hours. The modal class (1026 from a total of 2524) had a

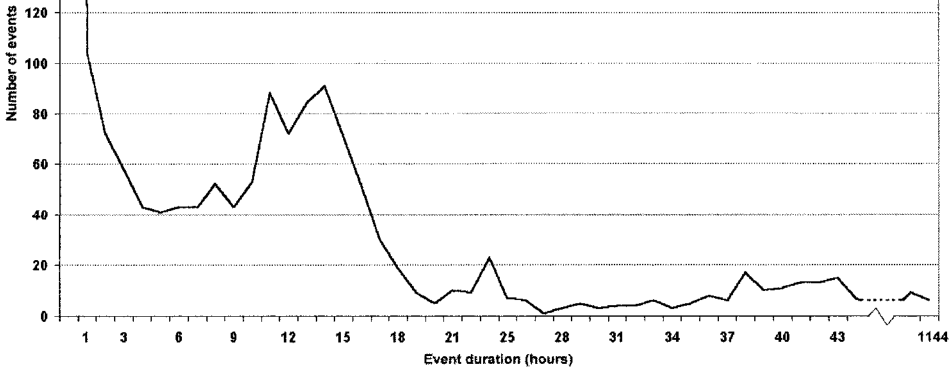

Figure 3. Event time span of non-residential burglaries in Central Nottingham (April 1995 to April 1997). The peak between 11 and 15 hours represents the period between a business closing and employees returning in the morning to find a burglary has been committed. The majority of incidents had a time span of one hour (or less) and this is probably due to the high number of alarmed premises that elicit a rapid police response. Note extended vertical and horizontal scales at the extremes.

time span of one hour or less and this is probably due to the high number of premises with burglar alarms that evoke a rapid police response.

To elicit a greater understanding of any spatiotemporal pattern accurate selection of records from the database has to be accompanied by clear graphical representation. A number of researchers have proposed different methods to visualise temporal change (Lowell 1994, MacEachren 1994, Peuquet 1994) including a snapshot approach that seeks to capture the existing state at a given moment (Peuquet and Niu 1995). Each temporal search can be considered as a slice extracted from a larger temporal continuity across which every incident exists at different times with varying time spans. The temporal continuity exists as a third dimension extending perpendicular to the two-dimensional plane on which each spatial object is located. This is shown in figure 4 where each column indicates the temporal time span and limits of the temporally unspecific event. The base of the column indicates the known start time of the incident, with linear time advancing vertically until the known end time is indicated by the top of the column. A shaded disk between the known start and end times indicates the place where the time snapshot of the temporal search intersects the two-dimensional spatial world. The weight attached to each spatial event can be depicted as either a different colour, shade, shape or line thickness. In the example presented in this paper the shade of the disk indicates the temporal weight: with long time spans the weighting has a low value, reflected by the lighter disk colour; with shorter time spans the weights have a higher value and are indicated by darker disks (figure 4).

When the process described above and outlined in figure 4 is applied to the example data from Central Nottingham, understanding of the spatial distribution of burglaries is enhanced by an ability to appreciate the probability that an event occurred within the time period. Figure 5 shows the boundary of Central Division of Nottinghamshire Police, with each point showing the location of each burglary with its corresponding aoristic weighting that might have occurred during the period

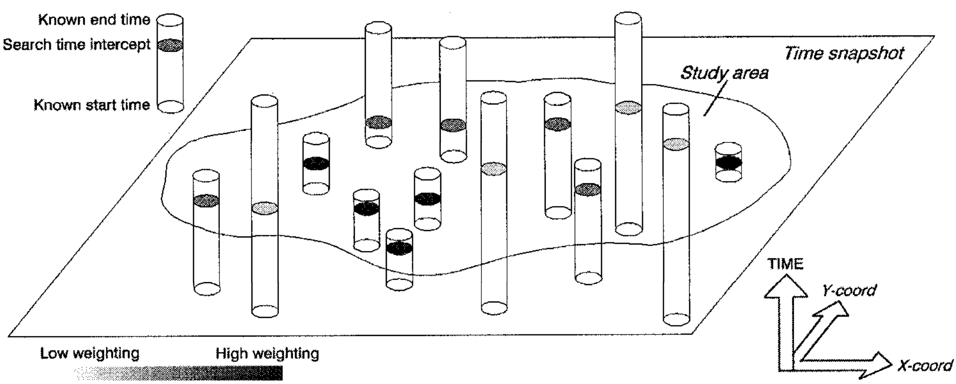

Figure 4. Graphical representation of aoristic weighting of temporally unspecific spatial attributes. The columns indicate the location of spatial objects that could have occurred at any time between a known start and known end time. The disks indicate the point of intersection between a search time snapshot encompassing the study area with the spatiotemporal objects. The shading of the disk indicates the value of the aoristic weight of each object. Objects with longer time spans have a correspondingly lower weight for each search period shown by paler disks, while shorter time spans with higher aoristic weights are indicated by darker disks.

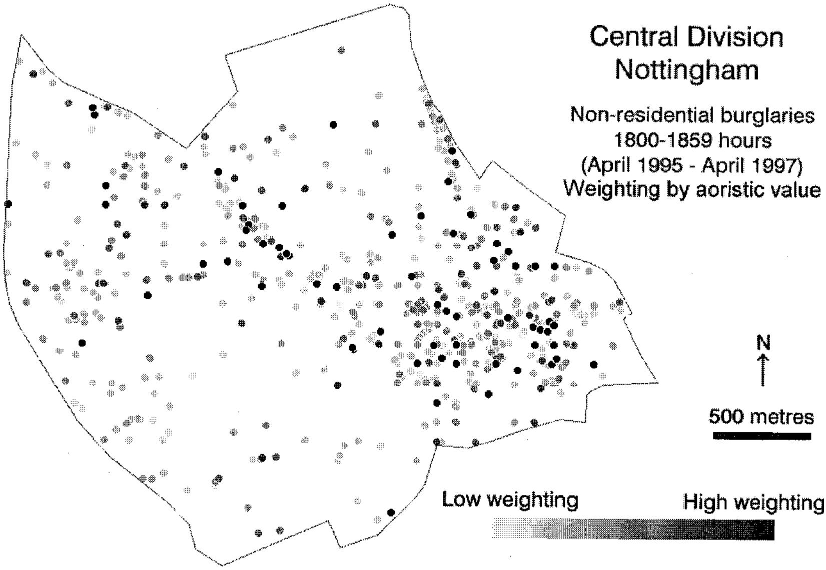

Figure 5. The distribution of non-residential burglaries in Central Nottingham for the period 1800 hours to 1859 hours over a two-year study period. Different shading of symbols indicates the aoristic weighting of each point (maximum value 1.0). The highest concentration of points are located in the Central Business District of the city in the south-east of the division.

1800 hours to 1859 hours. The distribution of points is concentrated in the Central Business District (CBD) of the city in the south-east of the division, with other concentrations being focused along arterial routes running north and north-west from the CBD. The apparent high number of properties in the CBD with high aoristic values may indicate that properties in these areas tend to have burglar alarm systems that are responded to quickly by the police service. Burgled premises in other areas might include shops, schools, community centres and churches that may have less effective security measures.

If the image in figure 5 can be considered as one ‘snapshot’ of the total probability of burglaries in the one hour period from 1800–1859 hours, then further snapshots can be pieced together to identify changes in the distribution of event probability that have occurred between snapshots. Like a strip of celluloid these snapshots can be compressed into an animation. This approach can generate very similar images where many points with lower aoristic values persist from one image to another. Another approach is to use surface generation techniques to simplify and smooth the display and remove subtle sources of interpretation error, such as points being obscured behind other points, and low aoristic value points being dominated out of the image by surrounding high value locations.

4. Surface generation

A number of surface generation algorithms are available for the analysis of point locations and this paper does not intend to review this considerable expanse of literature (Bailey and Gatrell 1995, Cressie 1993 or McCullagh 1988 could all act as a starting point). In the field of crime analysis ‘moving window’ techniques are popular and the following description outlines one method that can be formulated to include a temporal weighting. Other methods are also valid but the method presented here has been found to be successful by the author and is presented with the aim of providing a first benchmark for the aggregation and display of aoristic analysis results.

The 'moving window' technique employs a moveable sub-region (usually a circle) over the entire study area to measure dependence in subsets of the study area and is particularly suited to hotspot detection (Bailey and Gatrell 1995). A two-dimensional grid lattice which covers the entire study area with a rectangular grid of intersecting lines is defined and at each grid intersection circles are placed over the study area. Points falling within the circle are retrieved from the data to compute a value such as a density estimation. This process is shown in figure 6, where (*a*) shows a fictitious street network (grey) with the location of burgled premises shown as black dots. The moving window analysis approach is to superimpose a grid over the whole study area (*b*) and then at each grid intersection overlay a circle (or circles) of a predetermined radius (*c*)—commonly referred to as a 'bandwidth'. The crimes (points) falling within the circle are extracted and some form of algorithm is applied to extract a value. This could be a simple count of the number of crimes in the circle, a density calculation based on the number of incidents and the area of the circle, or some more complex algorithm such as a kernel estimation described by Bailey and Gatrell (1995).

This technique produces a more spatially smooth estimate of the variation than can be obtained with a fixed quadrat system such as the choropleth mapping technique. In addition to this the use of a moving window where windows overlap can help defeat much of the modifiable areal unit problem (Openshaw 1984, Unwin

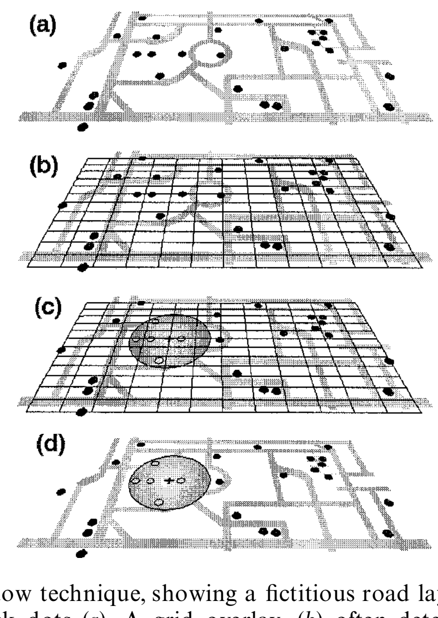

Figure 6. Moving window technique, showing a fictitious road layout in grey with burgled premises as black dots (*a*). A grid overlay, (*b*) often determined by the minimum bounding rectangle (MBR) of the points is searched at each grid intersection to determine how many points are identified within a certain radius (bandwidth) of the grid intersection, (*c*). Once these points have been isolated, (*d*) an algorithm can determine a value for the grid intersection based on a function of the points within the search circle.

1996). It is also a local spatial analysis method in a crime analysis environment where global methods are difficult to justify, due to the short distances that most burglars are known to travel to commit crime (Brantingham and Brantingham 1981, Brown 1982).

In each of the density calculations however, no account is taken of the relative location of events within the search window. Density calculations can be a useful tool, though an improvement is the ability to calculate an intensity measure such as a kernel estimation. This practice replaces the simple counting mechanism already described with a 'moving three-dimensional function (the kernel) which weights events within its sphere of influence according to their distance from the point at which the intensity is being estimated' (Gatrell *et al.* 1996, p. 259).

The three-dimensional function scans within the search circle and not only detects points within the search region but measures their influence and calculates their contribution to the intensity of the search relative to their proximity to the centre of the search circle. The closer an event is to the centre of the circle, the greater its contribution to the intensity reading.

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

The choice of suitable algorithm for the search parameter has, according to Gatrell *et al.* (1996), little bearing on the resulting intensity estimate. In the quartic kernel algorithm shown at (1), s represents the centre of the search circle, τ the bandwidth and d is the distance of each point (i) within the bandwidth (τ) from the centre of the search area (s). The calculation of the intensity $\lambda_\tau(s)$ is therefore the summation of the intensity of those values which have a smaller distance from s than d, where the intensity is weighted, with values at the centre weighted by $3/\pi\tau^2$, dropping smoothly to a value of zero at the maximum distance τ. This has been suggested as a reasonable choice and useful in a variety of typical applications (Bailey and Gatrell 1995, p. 85). The function shows a weighting that favours points close to the centre of the circle and decays smoothly towards the perimeter.

4.1. *Introducing an aoristic temporal weight*

An adaptation of this process is to include a temporal weight into the algorithm alongside the spatial weight. This is a fairly simple process whereby the unit value of each point in the spatial matrix is replaced by the temporal weight as calculated by the aoristic analysis. A suitable weighting system for this type of analysis is to standardise each point such that the total of all weights for 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:

$$\sum_1^n \sum_1^q t_i = n \quad \text{where} \quad \sum_1^q t_1 = 1$$

This modifies the intensity algorithm to include the temporal weight as:

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

In this manner each point in the spatiotemporal analysis includes a temporal weight and a spatial weight. This process was applied to the example data from

Central Nottingham and the spatiotemporal analysis had a discernible spatial resolution (50 m for each grid square) and a temporal probability resolution (1 hour). Figure 7 shows the hourly mid-afternoon (1500 hours) to early evening (2000 hours) pattern of non-residential burglaries for Central Nottingham where the surface generation process has employed an aoristic weighting. The intensity of aoristic values across the study area can be seen to increase as stores and businesses close for the evening.

5. Concluding remarks

As frameworks for the handling of spatial data become routine, the need for similar structures for temporal examination are becoming apparent. Temporal objects (or spatial objects with temporal attributes) can be incorporated and interrogated with temporal logic (Yuan 1997) and can be managed by temporal database systems and queries. However inflexible temporal database structures have limitations and there is a need in some areas for a less rigid approach. More fluid dimensions of time are necessary in order for GIS to become a more flexible platform to analyse problems such as spatiotemporal crime distribution.

Although Yuan suggested that 'many advantages result from modelling semantics (thematic attributes), time, and space (locations) separately in a GIS' (Yuan 1997, p. 742) aoristic analysis can provide a structure for the integrated analysis of space and time in temporally unspecific spatial variables, while still maintaining the flexibility that Yuan desired when making the above statement. Spatiotemporal aggregation can be used to simplify and visualise complex variables and convey greater meaning, often to non-technical audiences.

The use of aoristic analysis does assume that the probable time of event occurrence is evenly distributed between the start and end times. In some situations this assumption may not be valid, in that throughout a day vehicle thieves may avoid times when the streets are busy (early morning, lunchtime and evenings) and focus their activities to mid-morning or afternoon. Users of this technique may wish to enhance the model by including additional case-specific information, however even without this extra input an aoristic analysis compensates for events with a long time span by giving greater weight to events with shorter time spans.

Because of the fractional weightings used, some users without a statistical background may not fully comprehend the conceptual framework of the technique. In the author's particular field the application of aoristic analysis can aid police officers to understand better the temporal pattern of high volume crime and plan patrols and crime prevention strategy accordingly. Some accompanying explanation might however be required to explain the aoristic concept and why in any search period a

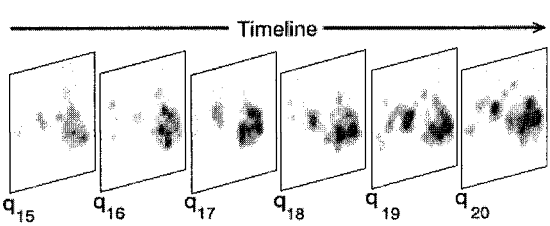

Figure 7. Six temporal surface snapshots generated from aoristic weightings. The images show an increase in the burglary accumulated probability in the study area as businesses close for the evening.

crime event does not necessarily carry a value of one, nor why a sum of all crime found and weighted by the selection process does not equate to a whole number.

'The alternative conceptualization of space and time will be one of the most important cornerstones for the implementation of the next generation of GIS' (Sui 1998, p. 661). Any next generation of GIS must incorporate a more flexible approach to dimensions of space and time if they wish to respond to the growing needs of users, and allow implementation of new more realistic models of a rapidly-changing world. Aoristic analysis can form the basis of structured integrity rules that permit a flexible approach to temporal analysis that can respond to a variety of temporal scales, resolutions and data accuracy.

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