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Research Article

Visualising Crime Clusters in a Space-time Cube: An Exploratory Data-analysis Approach Using Space-time Kernel Density Estimation and Scan Statistics

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Abstract
For an effective interpretation of spatio-temporal patterns of crime clusters/hotspots, we explore the possibility of three-dimensional mapping of crime events in a space-time cube with the aid of space-time variants of kernel density estimation and scan statistics. Using the crime occurrence dataset of snatch-and-run offences in Kyoto City from 2003 to 2004, we confirm that the proposed methodology enables simultaneous visualisation of the geographical extent and duration of crime clusters, by which stable and transient space-time crime clusters can be intuitively differentiated. Also, the combined use of the two statistical techniques revealed temporal inter-cluster associations showing that transient clusters alternatively appeared in a pair of hotspot regions, suggesting a new type of "displacement" phenomenon of crime. Highlighting the complementary aspects of the two space-time statistical approaches, we conclude that combining these approaches in a space-time cube display is particularly valuable for a spatio-temporal exploratory data analysis of clusters to extract new knowledge of crime epidemiology from a data set of space-time crime events.

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1 Introduction

Spatial epidemiological analysis of crime, with the aid of a geographic information system (GIS) and spatial statistics, is now widely used for analysing mass behaviours of crime events to reveal uneven distributions of crime risks and spatial interaction between crime events (Chainey and Ratcliffe 2005, Goldsmith et al. 2000, Turnbull et al. 2000). Much effort has been devoted to detecting geographic domains with high crime density – crime clusters/hotspots – and identifying their locations on maps. This article is intended to contribute to extending crime analyses from the spatial perspective to a spatio-temporal one, by proposing an exploratory method to comprehend space-time patterns of crime clusters using space-time statistics and 3D visualisation techniques.

A number of studies have highlighted the importance of temporal aspects in crime concentrations (Johnson et al. 2008, Paulson and Robinson 2004, Ratcliffe 2004). Johnson et al. (2008) showed that differentiating stable and fluid hotspots is crucial for identifying appropriate crime reduction responses. For example, short-term or cyclic clusters would require a quick strategic action using policing resources, while stable clusters may require long-term efforts to modify social and built environments. However, less attention has been paid to the development of systematic analysis and representational methods of temporal dimensions, as compared to the geographic dimensions of crime epidemiology (Townsley 2008).

Mapping crime at different time periods is probably the most common method to detect temporal changes in the distribution of crime clusters. In some cases, a research design may naturally lead to a pair of periods to be compared for testing a hypothesis on distributional changes of crime incidence. For example, in order to assess the impacts of social and built environmental changes caused by a large transportation project on the geographical distribution of crime, Ceccato and Haining (2004) used spatial scan statistics to assess the difference in geographic offence patterns over two periods of time, e.g. before and after the construction of a bridge across the Sweden-Denmark border. To evaluate the success of crime prevention measures, Bowers and Johnson (2003) and Johnson et al. (2004) proposed generalised frameworks of statistical testing to compare numbers of crimes in predefined regions before and after the measures were implemented.

However, using only two predefined time intervals may present a risk of masking important aspects of temporal changes in the distribution of crime clusters, particularly for differentiating stable and fluid hotspots. Shimada (2004) observed that geographic locations of residential burglary cases detected by a local indicator of spatial association (LISA) moved essentially among four time periods, although the division of the entire study period into subperiods for identifying moving hotspots remained an arbitrary choice; i.e., the temporal intervals as well as the geographic boundaries were modifiable (Yule and Kendall 1950). To incorporate temporal information of crime incidence in crime analysis, Townsley (2008) proposed an explorative graphical device that exploits a 2D geographic map of crime incidence along with charts of annual and temporal crime trends in a user-selected rectangular geographic region. Although that method enables interactive examination of temporal profiles of individual clusters, a user has to decide on which part of the study region to focus for each individual cluster domain based on a traditional 2D map of accumulated crime incidence over the entire study period.

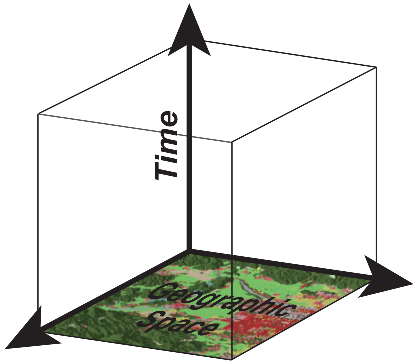

Figure 1 Space-time cube

Our approach proposed here is to create a three-dimensional map of crime events in a space-time cube to visually and simultaneously comprehend the temporal duration as well as the spatial extent of different crime clusters rather than focusing on an individual cluster. A space-time cube is a 3D space consisting of two horizontal dimensions of space (geographic plane) and one vertical dimension of time (Figure 1). The concept of the space-time cube originated in the time-geography diagrams (Hägerstrand 1970) used for the visual explanation of continuous space-time sequences of geographic objects; these diagrams have been extended to visualize various geographical events and motions in space-time (Kraak 2008).

Mapping crime events in a space-time cube is not a new idea. Brunsdon et al. (2007) evaluated possible space-time visualisation methodologies for crime data in an interactive visual environment, including the iso-surface methodology for analyzing the crime density estimated from the kernel density in a space-time cube. Considering that the iso-surface approach is just one option for visualising the space-time density in a space-time cube, we explore the further analytical potential of space-time cube visualisation by proposing new two approaches: (1) a space-time kernel density visualised by volume rendering (Levoy 1988); and (2) space-time scan statistics (Kulldorff et al. 1998a) for detecting significant space-time cylindrical clusters.

While the iso-surface approach requires selecting a specific density value to construct a 3D space-time contour surface (Brunsdon et al. 2007), volume rendering enables the simultaneous visualisation of distributions of different density values by controlling opacity and light effects (Levoy 1988). Thus, we consider that the volume rendering approach is a generalised extension of the iso-surface approach for visualising density estimates. In contrast to the kernel density approach, which is a non-parametric descriptive tool to obtain a smoothed density surface (Silverman 1986, Scott 1992), scan statistics can be a more confirmative tool, implying that we may obtain statistically confirmative information for identifying space-time domains of significant crime concentration. Scan statistics employ a scheme of rigid statistical testing under a given significance level in a multiple-test setting (Kulldorff 1997, Kulldorff et al. 1998a). Here, we use both methodologies to visualise spatio-temporal domains with a high crime density in a space-time cube employing 3D GIS and related technologies. We determine whether the combined use of these methodologies is effective for obtaining information regarding space-time crime epidemiology through an empirical data analysis of snatch-and-run offences reported in a city during two years.

The remainder of the article is organised as follows. In Section 2, we describe the dataset of crime occurrence space-time points used in this study. In Sections 3 and 4, we explain the methodologies of space-time visualisation based on space-time statistical techniques. In Section 5, we present the results of our data analysis and discuss their implications. We summarise and conclude in Section 6.

2 Data

The dataset used in our study consists of occurrence points of snatch-and-run offences reported to the Kyoto Prefectural Police during the period 2003–2004. Snatch-and-run offences are a type of robbery committed on the street. In most situations, offenders snatch purses or bags and escape on a motorcycle. There has been an increase in such street crimes, thereby worsening the general perception of public safety in the society of Japan (National Police Agency 2004). To address this problem, police departments widely adopted GIS crime mapping. For example, the Kyoto Prefectural Police established the Office of Crime Analysis (Yamane 2003) that has a GIS-based monitoring system to generate crime maps of major crimes, including street crimes and residential burglary, and disseminate these maps through the Internet.

Since street crimes commonly occur in built-up urban areas, we defined our study area as a collection of "half-divided grid squares" within the city planning area of Kyoto City (Figure 2). A half-divided grid square, which in Japan is designed as a small-area statistical unit, is roughly a 500 m × 500 m square cell (Statistical Bureau of Japan 2008). Therefore, we hereafter refer to this unit as a 500-m grid cell. The total number of reported crimes in the region during the two-year study period was 1,855. Each occurrence point is shown by a pair of *x*-*y* geographic coordinates and the month of occurrence. Although it is well documented that crime concentration exhibits a daily rhythm (Ratcliffe 2004, Townsley 2008), we did not consider such fine-scale fluctuations in the temporal dynamics of crime due to the limited temporal resolution of the supplied dataset. The monthly numbers of reported snatch-and-run offences in the study area did not show any clear upward, downward, or seasonal cyclic trends (Figure 3).

Figure 4 shows the data points mapped in a space-time cube, in which the *i*th offence is plotted on the (x_i, y_i, t_i) coordinate system. It should be noted that the vertical axis represents the time dimension, with the bottom and top positions corresponding to January 2003 and December 2004, respectively. At this point, the cognitive difficulty in comprehending meaningful space-time patterns in the point distribution becomes apparent, since it is difficult to judge the relative locations of points in a 3D space as compared to those in a 2D space. Thus, the use of statistical pre-processing of the point distribution, such as kernel density estimation (KDE), to generate clear visual effects is more important in 3D mapping than in conventional 2D mapping.

3 Space-time Kernel Density Estimation

3.1 Definition of Spatio-temporal Kernel

Kernel density estimation (KDE), devised for estimating a smooth empirical probability function (Silverman 1986), is now a commonly applied spatial analysis technique to

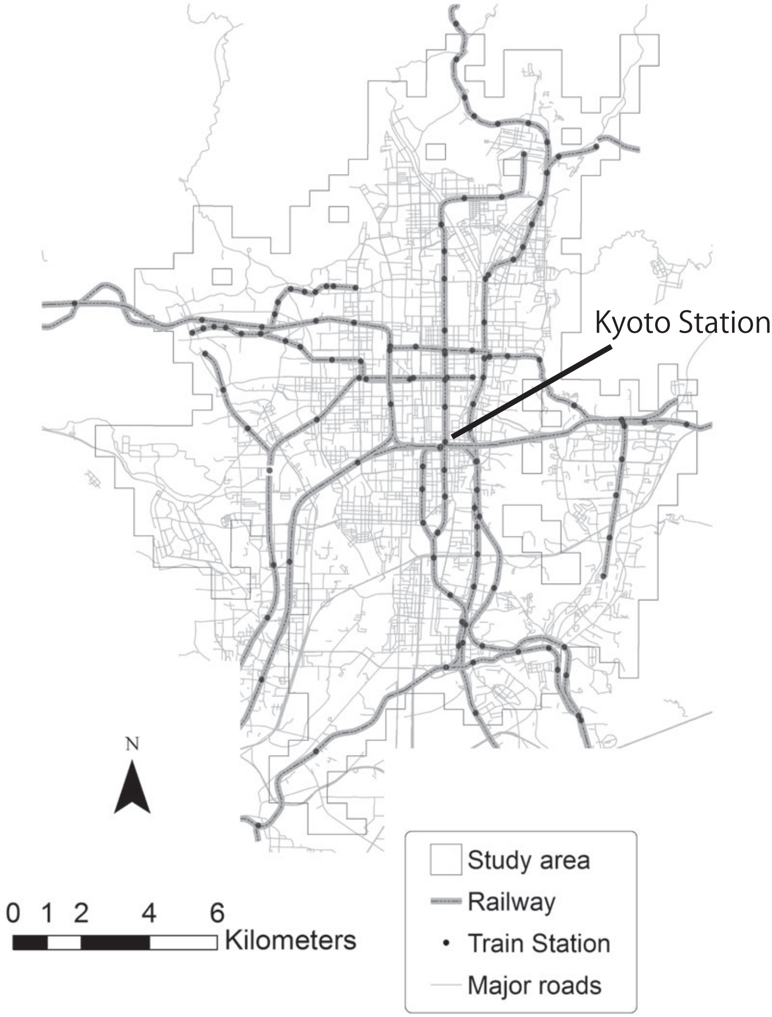

Figure 2 Study area

transform a geographically distributed set of points into a density surface in a GIS environment. Assuming a productive orthogonal relation between the space and time dimensions with a spherical relation between the two geographical dimensions, Brunsdon et al. (2007) have proposed its extension, the space-time kernel density estimate (STKDE), as:

$$\hat{f}(x, y, t) = \frac{1}{nh_s^2 h_t} \sum_i K_s\left(\frac{x - x_i}{h_s}, \frac{y - y_i}{h_s}\right) K_t\left(\frac{t - t_i}{h_t}\right), \tag{1}$$

where $\hat{f}(x, y, t)$ is the density estimate at location (x, y, t), n is the number of events, and h_s and h_t are the spatial and temporal bandwidths, respectively. In this study, the kernel

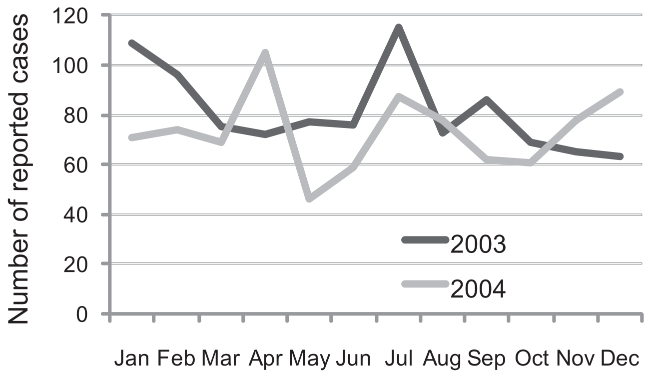

Figure 3 Monthly trends in reported cases of snatch-and-run offences, 2003–2004

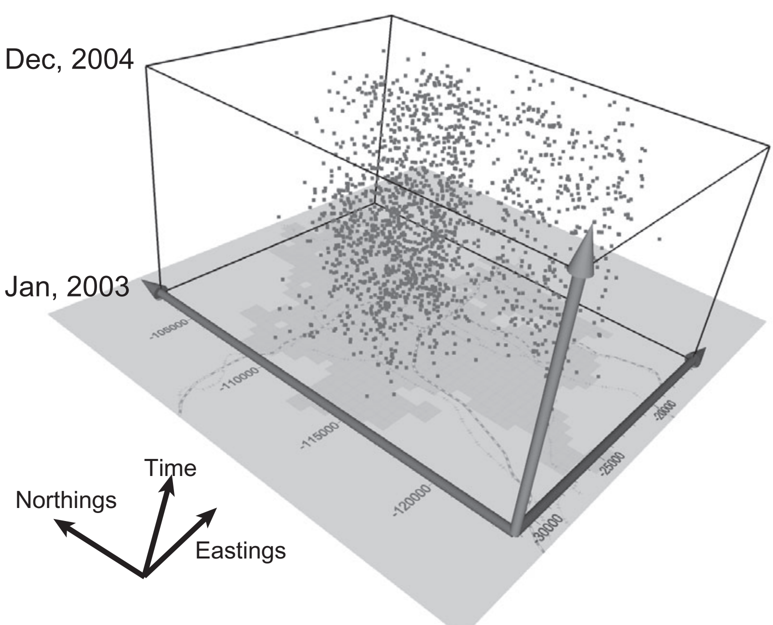

Figure 4 Space-time cube display of distribution of reported snatch-and-run offences

functions K_s and K_t are defined using the Epanecknikov kernel (Epanechnikov 1969), which is a common type of kernel function used in ArcGIS (ESRI, Redlands, California):

$$K_s(u,v) = \begin{cases} \frac{2}{\pi}(1-(u^2+v^2)) & (u^2+v^2)<1 \\ 0 & \text{otherwise} \end{cases}$$
$$K_t(w) = \begin{cases} \frac{3}{4}(1-w^2) & w^2<1 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

The domain in which the weight w is different from zero becomes a small space-time cylinder defined by the two bandwidth parameters h_s and h_t in a space-time cube. To implement STKDE, the entire space-time region is divided into small grid intervals, and then we calculate a weighted-density value of points within the space-time kernel centred on each grid point.

Although the KDE at a point corresponds to a probability value between 0 and 1, we easily obtain a density value in terms of the number of events per unit space-time ($h_s^2 h_t$) by multiplying the density estimate $\hat{f}$ by n for a more intuitive understanding.

3.2 Bandwidth Selection

A crucial element of KDE is the selection of the bandwidth parameters. The bandwidths control the degree of smoothness in an estimated density surface. A large bandwidth leads to a smoother surface to emphasize statistically stable behaviour, though it may smooth out small but important spatio-temporal fluctuations from the true density distribution. Although we could interactively choose appropriate bandwidths by looking at density estimates of different bandwidths for descriptive purposes, it is quite useful for a researcher if data-driven candidates of bandwidths are available as references for practical bandwidth selection.

Scott (1992) derives a plug-in estimate of optimal bandwidths for a multivariate productive kernel (d-dimensional Gaussian kernel) to minimise the asymptotic mean integrated square errors by assuming an orthogonal multivariate normal distribution. The rule can be considered as a simplified generalisation of Silverman's rule of thumb for one dimensional bandwidth selection (Silverman 1986). Scott's plug-in estimate is given as:

$$\hat{h}_j = n^{-1/(3+d)}\hat{\sigma}_j, \tag{3}$$

where $\hat{h}_j$ is the plug-in estimate of bandwidth for dimension j and $\hat{\sigma}_j$ is the estimate of standard deviation in the point distribution of the j^{th} dimension. By inserting $d = 3$ and a ratio of equivalent bandwidth size between Gaussian and Epanecknikov kernels derived from canonical bandwidths (Härdle et al. 2004), we obtain the following rule for 3D Epanecknikov kernel density estimation:

$$\hat{h}_k = 2.21n^{-1/7}\hat{\sigma}_k. \tag{4}$$

The estimate for $\hat{h}_s$ and $\hat{h}_t$ are obtained by a pooled standard deviation of the two geographic coordinates $\hat{\sigma}_s$ and a simple temporal standard deviation of occurrence time $\hat{\sigma}_t$, respectively. However, when a true distribution is non-normal, and in particular multimodal, the plug-in estimates are likely to be too large, causing excessive smoothing (Härdle et al. 2004). Thus, we should better consider the plug-in estimate as an upper limit of the bandwidth to be tested.

Another practical bandwidth selection approach that is popular for crime mapping is to use the average distance between the k^{th} nearest neighbour points (Chainey and Ratcliffe 2005, Goldsmith et al. 2000). Considering that the search limits for estimating a density value are defined by a space-time cylinder domain under the kernel used in this study, we define the space-time distance D_{ij} between points i and j as:

$$D_{ij} = \max\left(\|(x_i, y_i) - (x_j, y_j)\|, |z_i - z_j|\hat{\sigma}_s/\hat{\sigma}_t\right). \tag{5}$$

The temporal separation is scaled to that of the geographic separation by the ratio of standard deviations. Although the scale adjustment could be handled in a number of different ways, we tentatively adopt the ratio following Scott's rule. Letting $D(k)_i$ be the k^{th} nearest neighbour distance for the i^{th} point, calculated using equation (5), we obtain spatial and temporal bandwidths by choosing k:

$$\hat{h}_s(k) = \frac{1}{nk}\sum_{i}^{n}\sum_{l}^{k} D(l)_i,$$

$$\hat{h}_t(k) = \frac{1}{nk}\sum_{i}^{n}\sum_{l}^{k} D(l)_i\,\hat{\sigma}_t/\hat{\sigma}_s. \tag{6}$$

Since the value of k is often chosen around 20 for conventional 2D crime mapping for a city-wide geographic extent (Goldsmith et al. 2000, Harada and Shimada 2000), we use the estimates for $k = 20$.

3.3 Volume Rendering

As Brunsdon et al. (2007) noted, it is not straightforward to visualise STKDE due to its volumetric data structure given of four dimensional values consisting of a position vector (x, y, t) plus a scalar giving the estimated density. Volume rendering is a popular technique to visualise the entire internal structure of such volume data. The technique creates two dimensional projections of a shaded volume onto a screen space based on a hypothetical viewing point. An important element of the technique is that the degree of transparency is controlled to be high for low density regions so that low density regions are completely transparent or drawn like thin mist through which high density domains are visible as a shaded solid volume with colours graded according to the density values.

Since direct volume rendering was developed (Levoy 1988), numerical applications and technical advancements have emerged in various fields, and in particular in medical imaging where 3D images are constructed from many slices of information from a human body by computerized tomography scanning (Kaufman and Mueller 2005). We now give a brief description of the algorithm to obtain a 2D screen image from a volume dataset. First, each 3D regularly-arrayed point, called a voxel, is given an opacity value and an optical colour value based on its density value. These voxel values are numerically integrated along a ray line, called a rendering pipeline, that passes through the volume from the viewing point via each pixel of the screen image. To add a stereoscopic effect on the projected image, a shading model is applied to the voxel dataset from a hypothetical source of light. We implement the direct volume rendering of STKDE by Voxler (Golden Software, Golden, Colorado), a specialised application for interactive volume visualisation.

4 Space-time Scan Statistics

Spatial scan statistics are devised to detect significant clusters by exhaustively scanning over space using moving circular windows with different radii (Kulldorff 1997). Following the same concept, space-time scan statistics (STSS) employ cylindrical search windows in a space-time cube in order to seek significant spatio-temporal clusters (Kulldorff et al. 1998a). A cylindrical domain referred to as Z is defined as:

$$Z = \{(x, y, t) | (x - x_c)^2 + (y - y_c)^2 \le r^2, t_s \le t \le t_e\}, \tag{7}$$

where (x_c, y_c) is the geographical centre of the domain, r is the radius of the domain, and $[t_s, t_e]$ is the domain period. Whereas STKDE employs a small, fixed size space-time domain to obtain a smoothed hyper-surface of density, STSS tests various sizes of space-time cylindrical domains in terms of both geographical radius and temporal length.

By assuming that the expected number of crimes is geographically constant in the built-up area of the city, we apply the Poisson model of space-time scan statistics to a dataset consisting of crime event counts aggregated in each 500-m grid cell. The maximum radius of the cylindrical search window is set to 1 km based on a preliminary investigation of cluster sizes of the usual 2D crime mapping. Choosing the upper geographical search limit for scan statistics is crucial since it is well known that if it is too large, spatial scan statistics are likely to provide a few extra-large and low-risk clusters (Pfeiffer et al. 2008) that are generally useless for facilitating practical local policing activities.

The test statistic is the observed maximum likelihood ratio in a cylindrical window in the entire space-time domain under study. Omitting a constant term, the statistic is given as:

$$\lambda = \sup_Z \left(\frac{y(z)}{e(z)}\right)^{y(Z)} \left(\frac{y(z^c)}{e(z^c)}\right)^{y(Z^c)} I\left(\frac{y(z)}{e(z)} > \frac{y(z^c)}{e(z^c)}\right), \tag{8}$$

where y and e denote the observed and expected number of cases, respectively, Z and Z^c represent domains inside and outside the specified window, respectively, and I is the indicator function (if $a > b$, then I($a > b$) becomes 1, otherwise 0). Since the expected number of cases is proportional to the built-up area and the temporal duration of the specified window, the ratio y/e corresponds to the space-time density of crime occurrence within the space-time domain.

Under the null assumption that cases of the event under study randomly occur following a Poisson distribution, Monte Carlo replications of the dataset enable us to obtain the simulated distribution of the likelihood ratio statistics λ for significance testing of high density clusters. We generate 999 replications to obtain P-values, indicating the probability of the random appearance of an observed high crime density in a cylindrical window. The cluster defined by the cylindrical window with the lowest p-value is called the most likely cluster. Secondary clusters are also obtained for clusters that do not geographically overlap more likely clusters if their P-values are below the significance level. Whereas classic methodologies using a window-based search for statistically significant clusters, such as with the Geographical Analysis Machine (Openshaw et al. 1987), suffer from multiple-testing problems since they repeat local evaluations of anomalous values countless times, scan statistics provides a way to avoid the difficulty by focusing on the maximum value in the entire study domain. However, the significance of the clusters obtained by STSS is correct only for the most likely cluster; for secondary clusters the method provides conservative results. Thus, for exploratory purposes, we extract clusters based on the 10% level as well as the conventional 5% level. By passing the result from SaTScan 5 (Kulldorff et al. 1998b), a tool to implement space/space-time scan statistics, to the 3D GIS environment ArcScene (ESRI, Redlands, California), we can easily visualise significant space-time clusters as solid cylinders.

5 Evaluation of the Two Methodologies

5.1 Visualisation Results

STKDE is carried out using the bandwidths suggested by the plug-in estimate and the 20th nearest neighbour distance (k = 20), giving the vector of geographic and temporal bandwidths as (2.42 km, 5.37 months) and (1.01 km, 2.25 months), respectively (Figure 5). The volume-rendering image generated using the plug-in estimate clearly shows a tendency of over-smoothing and exhibits only large-size clustering in the central part of Kyoto. The density distribution based on the 20th nearest neighbour distance (k = 20) shows more detailed clustering exhibited in two general trends. High-density domains appear around Kyoto Station and the central part of the city as "pillars" or "cumulonimbus", stretching from the bottom to the top of the space-time cube. This implies that the density of crimes reported in these geographical regions is constantly high. In contrast, transient "floating island" clusters that appear as high-density regions but for a shorter temporal duration are identified around several sub-urban railway stations.

As in the case of two-dimensional crime mapping, a caveat of STKDE is that the technique may exaggerate high-density regions (Chainey and Ratcliffe 2005). High-density regions appear even if almost no cases are observed inside the region, particularly when a large bandwidth is applied (Figure 5a). We note that the colours and opacity classification are different for the two bandwidth cases, since the large bandwidth derived by the plug-in estimate reduces the density range and could ambiguously show a few transient clusters with very low density values.

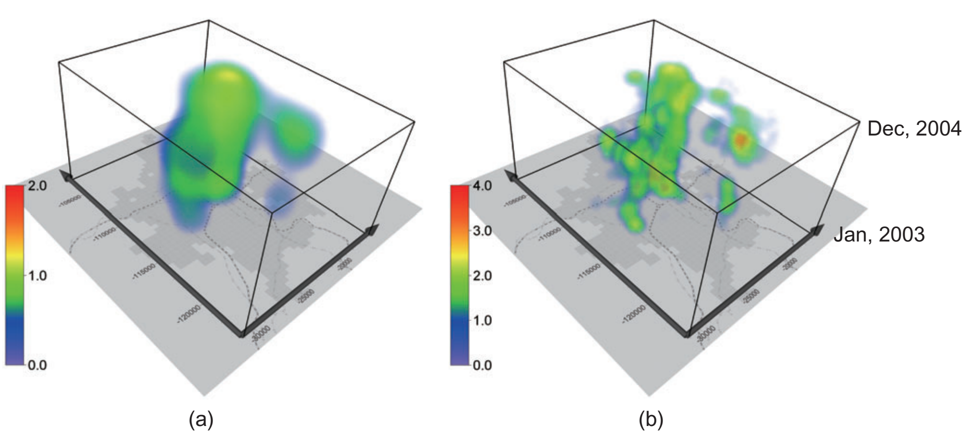

Figure 5 Space-time display of volume-rendering results of estimated space-time crime density (number of cases per square kilometre per month). (a) Plug-in estimate (b) Average 20th nearest neighbour distance
Note: The lowest density domain, where the density is less than 0.4 in (a) or 0.8 in (b), is controlled so that it is completely transparent in the space-time cube displays.

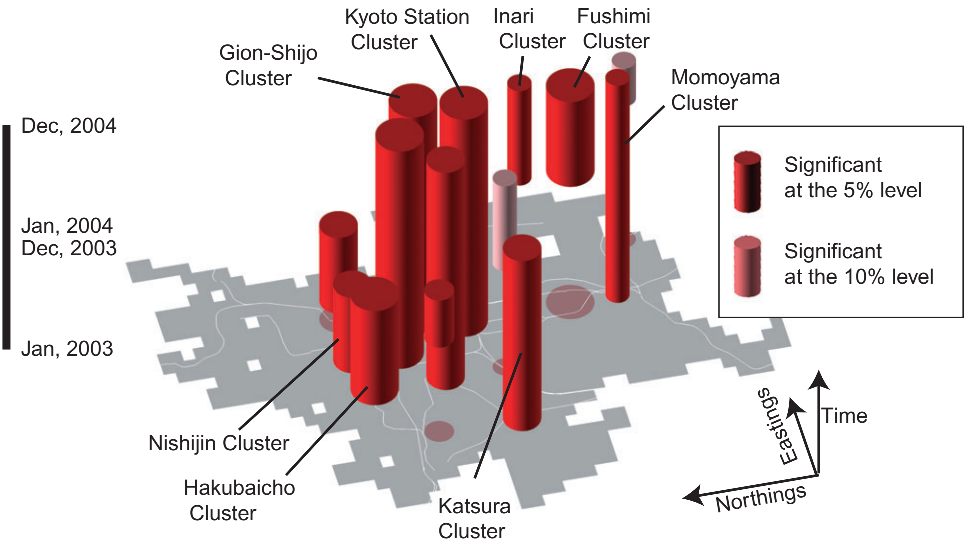

Figure 6 Space-time display of significant high-density clusters detected by space-time scan statistics

Figure 6 shows the significant clusters obtained by STSS in the space-time cube. The two aspects of spatio-temporal clusters shown by STKDE – the stable pillar and the fluid floating island clusters – can be clearly identified from the STSS. We believe that STSS gives a statistical confirmation of the crime clustering obtained by STKDE.

The constant high crime density in and around Kyoto Station (the largest railway station in the study area) and the central part of the city reflects the concentration of a large number of people on streets who are potential victims, the ease with which a criminal can escape into high-density traffic, and the high degree of anonymity in the urban environment. Another overall trend is that several transient clusters in the northern part of the city disappeared in the latter half of 2004 (e.g. Nishijin and Hakubaicho clusters in Figure 6, while a number of transient clusters emerged in the southern part of the city in 2004 (e.g. Inari and Fushimi clusters in Figure 6). This might be related to a displacement phenomenon of crime; that is, local crime prevention actions in the northern part of the city in 2003 might have pushed the crime clusters toward the southern part of the city in 2004. However, since numerous formal and informal policing activities were conducted in various ways during that time period, it is difficult to judge which specific activities were responsible for the transient nature of the clusters.

5.2 Utility of Combining the Two Approaches

Although the two approaches used to visualise crime clusters exhibit similar trends, the two approaches complement each other in a practical analysis. Hence, combining the two approaches may provide valuable new information on space-time clustering of crime. STSS provides more clear-cut images of space-time clusters, reflecting the black and white nature of significance testing, wherein significant cylindrical domains are shown as solid objects. We stress, however, that the method assumes that the geometrical structure of space-time clusters is in the form of a space-time cylinder. Conversely, STKDE involves a minimal geometrical assumption regarding the structure of clusters by using a reasonably small cylindrical kernel to fuzzily visualise high-density domains. Thus, it is reasonable to assess the validity of the assumption in STSS from the result of STKDE. As Figure 5b indicates, space-time concentrations of high-density regions are adequately described by approximately cylindrical domains in a space-time cube, particularly for the case of pillar clusters.

Another important aspect of the description by STKDE is that the density surface keeps the information on the intensity of crime concentrations calculated as space-time density within a cluster domain. In contrast, such intensity information is lost in the output from STSS. An example can be seen in a pillar cluster where vertically changing colours indicate that crime concentrations are changing over time, even if the crime density in the region is always significantly higher than that in other regions. Although inter-cluster relationships of such changing densities may give important clues to comprehend the space-time interaction of crime, the relationships between many clusters cannot be easily determined only through the visual images of STKDE.

Therefore, we assessed inter-cluster associations through temporal correlations of monthly crime incidence among the circular geographic domains detected by STSS (hereafter referred as "cluster regions"). Using the monthly numbers of crime occurrence in each cluster region for the study period (24 months), we computed the Spearman rank correlations of the monthly series of crime occurrence between every pair of cluster regions. Figure 7 shows the resulting significant inter-cluster correlations at the 5 and 10% level. In the central part of the city, including Kyoto Station, four cluster regions are positively correlated, indicating a synchronised temporal trend of crime density among the regions. These results suggest that four clusters form a large, irregularly shaped cluster sharing the same temporal trend of crime occurrence. Another weak synchronisation of crime occurrence might exist in the western suburbs of the city. Recently developed techniques of STSS that allow irregularly shaped regions as potential clusters (Tango and Takahashi 2005) might automatically detect these interrelated adjacent clusters as one object. However, circular scan statistics with a reasonably small upper search limit would provide another, more intuitive and less computationally intensive method to identify irregularly distributed, high-density regions as clusters to be highlighted.

A more important finding was a significant negative correlation between the Katsura and Momoyama cluster regions. This result indicates that when the crime level in a cluster region increases, crime level in the other cluster region decreases, and vice versa. A detailed image obtained by KDE vividly shows clusters of snatch-and-run offences appearing alternatively in the two regions (Figure 8). We stress that this space-time visualisation is vital for recognising the temporary association between the two hotspots, since there are other possible patterns producing the same negative correlation (e.g. a situation where the number of crimes in one region keeps decreasing and that in another region keeps increasing during the entire study period).

STSS fails to capture the alternative trend, partly because the likelihood axiom in the technique leads to the creation of large/long clusters containing large numbers of cases even if the risk within clusters often becomes low. Another reason is that the algorithm of SaTScan is designed to detect only one cluster for each geographic location, which reflects the development of the technique from spatial cluster detection.

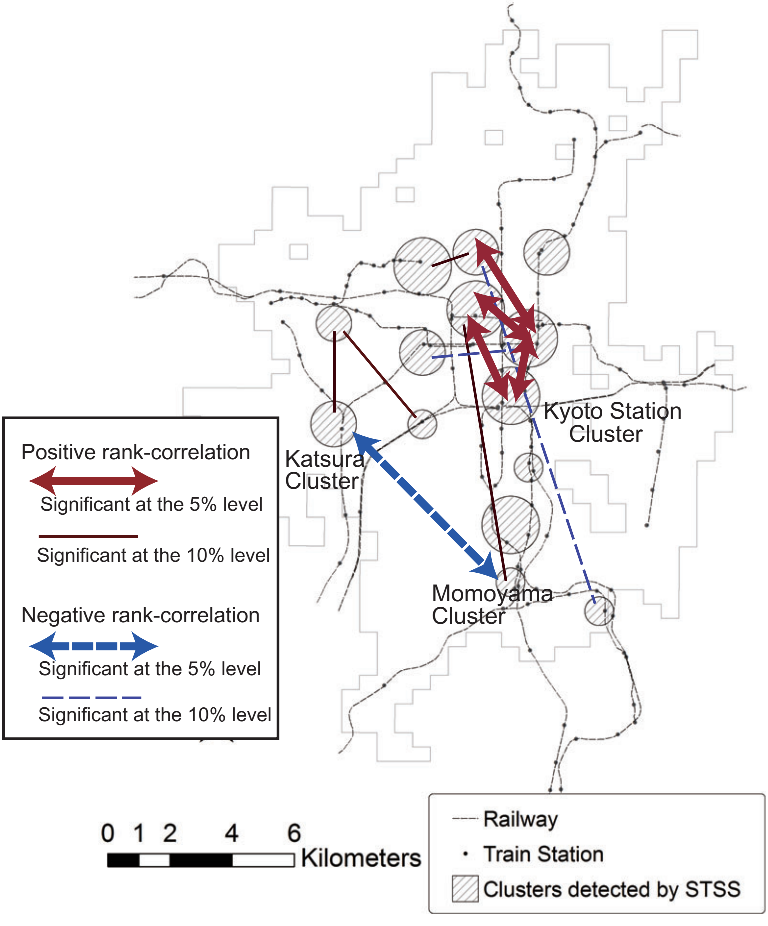

Figure 7 Spearman's rank correlations of monthly case numbers among cluster regions detected by spatial scan statistics

The phenomenon of alternating clusters or hotspots can be interpreted to result from the rational choices of crime offenders interacting with local policing activities (cf. Piquero and Tibbetts 2002). A classic explanation for crime displacement is that offenders change their activity to avoid local police and the informal crime-prevention activities that are often intensified after a crime outbreak begins in a local area (Paulson and Robinson 2004). However, acquiring local knowledge of a different region would be costly for offenders. Considering that the level of formal and informal local policing activities decreases after a certain period, it would be a rational decision for offenders to target multiple known geographic regions with a sufficient time interval to avoid local police activities, thereby committing crimes repeatedly and efficiently. In Figure 8, the hypothetical displacements of crime hotspots are shown by arrows. This result highlights the importance, in designing effective preventive actions against this crime, of monitoring clusters of snatch-and-run offences by evaluating the space-time relationships in a widespread space-time context between areas of elevated risks.

To verify this interpretation that suggests a new type of crime displacement, more evidence should be accumulated in terms of collective and behavioural aspects of crimi-

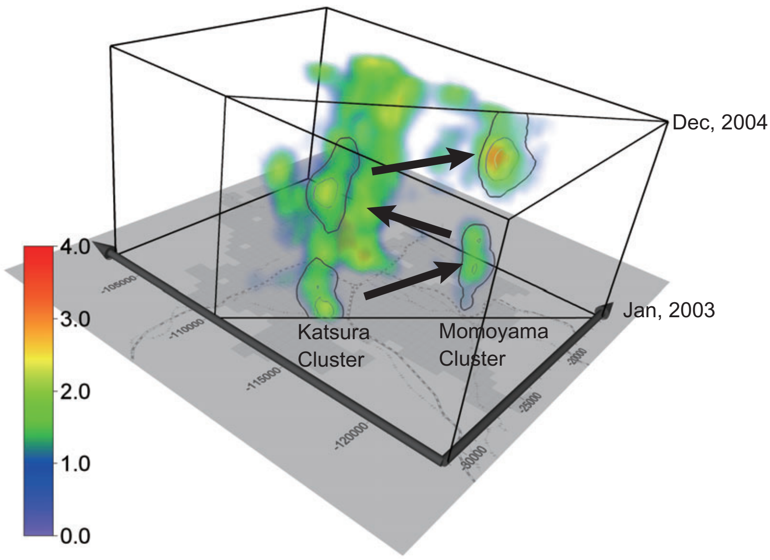

Figure 8 Alternating occurrence of crime clusters in a pair of cluster regions. The density is estimated from the average 20th nearest neighbour distance, as in the case shown in Figure 5b. A space-time plane passing through central locations of the pair of regions is denoted by contour density lines and arrows indicating a hypothetical movement of a crime hotspot

nal offences. However, it should be noted that the result discussed above, which was obtained through space-time cube visualisation, sheds new light on the possibility of obtaining a new interpretation of space-time interaction observed in crime epidemiology. This interaction could not be easily identified using previous statistical approaches to detect the general behaviour of space-time crime clustering or the neighbourhood effects of repetitive crime, regardless of whether the risk of crime victimisation is elevated in a neighbourhood (Grubesic and Mack 2008, Johnson et al. 2007). The alternative view of crime occurrence offered by our research provides a new component to be taken into account for predictive epidemiological modelling of clusters or hotspots (Cohen et al. 2007, Johnson et al. 2009, Lawson and Kleinman 2005).

More importantly, we see a general implication for spatio-temporal data analysis in the effectiveness of combining descriptive and confirmative space-time statistics in an interactive space-time visualisation environment. Neither of the two statistical techniques alone, nor space-time display alone, is sufficient to identify the alternating crime clusters identified in our research.

6 Conclusions

We have described a new approach for crime mapping using a space-time cube wherein a spatio-temporal density distribution can be visually explored in an interactive 3D GIS environment. The proposed 3D space-time crime mapping enables effective simultaneous visualisation of the geographical extent and the duration of crime clusters. Compared to the traditional temporal crime mapping performed using cross-sectional maps with arbitrary time intervals, this new 3D method using a space-time cube is particularly useful in differentiating stable and fluid crime clusters as well as in identifying the geographical diffusion and movement of crime clusters.

Our visualisation methodology is designed to use descriptive and confirmative space-time statistics, which are the space-time kernel density estimation (STKDE) and space-time scan statistics (STSS), respectively. These two methodologies of space-time statistics used for 3D mapping are complementary. STSS rigidly specifies crime cluster domains that can be used for secondary analysis, such as evaluating temporal correlations of cases between detected cluster domains. However, the 3D method assumes that space-time domains of crime clusters are cylindrical. Three-dimensional mapping using STKDE draws fuzzy domains, indicating areas of high crime density but without clear boundaries. It can also be used to verify the assumption of STSS and to investigate more detailed space-time sequences of crime clusters. This is in contrast to the visualisation of STSS that statistically confirms anomalous concentrations of cases but might oversimplify the distribution of space-time concentrations.

Our empirical analysis of the snatch-and-run offences dataset of Kyoto City revealed consecutive stable clusters during the study period in the central part of the city and around Kyoto Station, as well as transient clusters around several suburban railway stations. Temporal differences in the transient clusters that alternate between two cluster regions suggest a new type of displacement phenomenon that may be caused by the rational behaviour of crime offenders to efficiently commit crime by reusing known crime scenes.

The proposed approach can be used for analysing other cases of crime epidemiology, highlighting different temporal aspects such as weekly and daily patterns of crime occurrence. It may also be used in other types of fields, including the epidemiology of diseases. It may require a further improvement of the approach to consider space-time variations in the population at risk as well as those in event densities for detecting clusters based on elevated population risks. Another important future technical challenge is to integrate the visualisation approach employed here with developing network-based space-time statistics reflecting a recent shift in spatial analysis from planar to network space (Okabe et al. 2006), particularly for a detailed analysis in a smaller geographic setting. Another direction of further research could be to link the findings from visual explorative data analysis to predictive modelling. Our empirical analysis suggests that systematic space-time interactions of crime occurrence would emerge among non-adjacent regions. Compared to a recent development in techniques and applications of 3D GIS/geovisualisation, Batty and Longley (2003) argued that the development of 3D spatial analysis in these new 3D environments was still underdeveloped. Space-time data analysis through space-time cube visualisation is a promising approach because it can provide a new toolbox for 3D spatial analysis in the era when 3D geovisualisation is widely available in a GIS environment that integrates various space-time information, such as individual space-time paths and constraints on behaviours (Kwan 2004), as well as the collective risk estimated by event densities.

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