

Chapter 13

A Method of Visual Analytics and Data Visualization in Design Context: Case Study of Spatiotemporal Data Visualization of Urban Retail Agglomeration Growth



Akiyoshi Inasaka

Abstract Urban commercial facilities significantly influence neighborhood residents, with changes like store closures disrupting their routines. Especially for the elderly, proximity to these facilities is crucial. Although introducing well-known brands can rejuvenate areas, they might also lead to overcrowding, potentially diminishing the quality of life for locals. It is imperative in urban planning to understand these dynamics and their implications. This chapter delves into the formation of commercial clusters in urban zones and introduces techniques for analyzing and visualizing these trends. Utilizing data from Shibuya Ward, Tokyo, the study demonstrates the efficacy of these methods. The analysis focuses on the expansion direction of commercial clusters using spatiotemporal point data. By tracking when each store opened, the research identifies how new establishments influence the growth trajectory of existing commercial conglomerates. Using a circular statistical method, the study visualizes the expansion of commercial clusters.

Keywords Visualization · Spatiotemporal data · Circular statistics · Retail agglomeration

This contents of this paper are based on the following papers originally published in a Japanese journal: Inasaka, A. and Sadahiro, Y. (2010): A Method of Analysis and Visualization of Expanding Direction of Retail Distribution, *Transactions of AIJ, Journal of Architecture Planning and Environmental Engineering*, Vol.75, No. 650, pp.889–896 (in Japanese). Inasaka, A. (2013): Visualization of Expanding Direction Pattern of Retail Distribution using High Resolution Spatiotemporal Data, *The 36th Symposium on Computer Technology of Information, Systems and Application of Architectural Institute of Japan*, pp.265–268 (in Japanese).

A. Inasaka (✉)

Department of Design, Faculty of Creative Engineering, Chiba Institute of Technology, Narashino, Chiba, Japan

e-mail: akiyoshi.inasaka@p.chibakoudai.jp

13.1 Introduction

13.1.1 Urban Events as Manifestations of Urban Activities

In urban space, many spatial phenomena manifest people's diverse urban activities. These events have various effects on urban activities, affecting other urban activities. Some of these events affect people's daily lives directly or indirectly. In particular, in urban commercial areas, people's daily lives are intermingled with urban activities that are easily influenced by social conditions, such as commercial activities, and the effects of each of these activities are significant. There are two major types of events in urban commercial areas: visible events that can be seen with the naked eye and invisible events that cannot be seen with the naked eye. The first type of invisible phenomenon is typical of each region's unique atmosphere and image. Although invisible to the eye, they are important indicators for people to choose a good place to live or to verify the affinity between the image of a store and that of the local area. They should be understood when people make important decisions about urban activities.

On the other hand, visible events include, for example, various construction activities such as new building construction and remodeling and the accompanying store closings and vacancies. It is necessary to understand exactly how these activities are manifested and positioned in urban planning to create a harmonious streetscape and a convenient commercial area for residents. Thus, urban events are important in all urban activities, including residents' lives and urban planning, and must be accurately understood.

Many of the urban events mentioned above can be grasped and understood to some extent by reading various spatial data provided by government and public agencies, such as numerical maps, census data, various statistical data, data from basic urban planning surveys, and residential maps and telephone directories provided by private companies. In recent years, with the development of information technology and ubiquitous technology, it has become possible to obtain more detailed spatial data on events in a given location than was previously possible, and data that captures time-series changes at the same location has also been developed. However, displaying a large amount of detailed data does not always accurately capture the essential events. For example, a large amount of data may be graphically close together, densely packed, or overlapping, and the essential event that is being captured may be buried. It is necessary to select, aggregate, or transform the information necessary to capture the essence of the event and perform operations to remove excess information (Monmonier and Watanabe 1995 "How to Lie with a Map"). This study defines visualization as displaying information extracted from such operations.

13.1.2 Visualization Methods Using Large Amounts of Spatial Data

Exploratory Spatial Data Analysis (ESA), which utilizes Geographic Information Systems (GIS), has attracted attention in recent years as a method for clarifying phenomena from a large amount of detailed spatial data. Among them, visualization methods are very versatile for two reasons: visualization of information allows for quick and easy verification of more information, and graphical representation allows non-specialists to deepen their understanding of the data intuitively. The graphical representation allows non-specialists to understand the data intuitively (Haining 2003).

Numerous studies have been conducted in various fields on spatial data visualization methods. Here, we will discuss the different types of spatial data and their visualization methods. Specifically, spatial data is divided into low-dimensional spatial data with relatively few attributes and variables ranging from one to three dimensions and high-dimensional spatial data with various variables and attributes of four or more dimensions. The visualization method is organized along two axes: non-spatial visualization, such as graphs and tables of aggregate data, and visualization, in which spatial relationships can be seen on maps. (Table 13.1).

13.1.2.1 Low-dimensional Spatial Data, Non-spatial Visualization

It refers to the visualization of the results of aggregation or statistical processing of data provided in tables, such as census data or various statistical survey data at a certain point in time, by extracting specific attributes or items of the data and visualizing the trends among the data utilizing a numerical line for one-dimensional data, or a two-dimensional or three-dimensional scatter diagram for two-dimensional or three-dimensional data. For one-dimensional data, it is possible to visually capture the trend among the data through a number line. This also applies to histograms, which display data aggregated by section. Methods that belong to this category are used to grasp relationships that do not depend so much on the position of the data as on the attributes of the spatial data or the values of the variables. Since this type of method is generalized and there are abundant research examples, we will not go into detail in this study.

Table 13.1 Organization of existing visualization methods

	Non-spatial	Spatial
Low dimension	Scatterplot, histogram, and	Map, cell, 2D + 3DCG, area cartography Area cartogram
High dimension	Line plot, parallel Coordinate plot)	3DCG, VR, 2D + 3D animation Space syntax

13.1.2.2 High-dimensional Spatial Data, Non-spatial Visualization

This type of data and visualization refers to the visualization of the results of aggregation or statistical processing of comparing various attributes and items and their time-series changes in the census and statistical survey data, as described above. Many of the methods in this category capture the relationships among multiple attributes and variables of data as time-series transitions and changes. For example, in chemistry and physics, data capturing time-series changes of a certain substance, and in statistics, visualization of time-series changes of a certain variable value. In recent years, with the development of information technology, various types of data have become more detailed and voluminous, and the non-spatial visualization methods for low-dimensional spatial data described above are no longer sufficient to handle them. A method for efficiently understanding such multi-attribute and multi-variable data in a unified manner is needed, and many studies have been conducted.

There will be a tool to unify three types of plots: parallel coordinate plots by Gahegan (2005) that capture the variation among variables, scatter plots that look at correlations among multiple attribute variables, and plots that capture distribution trends such as variance, skewness, and kurtosis for each variable's data. kurtosis) of each variable. As an example of its application, an attempt has been made to display the obtained results on a map (e.g., Theus 2005).

13.1.2.3 Low-dimensional Spatial Data and Spatial Visualization

It targets visualization based on the spatial positional relationship of each data, which the above-mentioned non-spatial visualization methods cannot capture. In addition to the census and statistical data described above, this method is used to visualize spatial data that captures spatial and geographical conditions and characteristics, such as topographic elevation data, road maps, and building maps. Many of these methods are based on maps. This type of research is conducted using GIS in cartography and geovisualization.

A GIS visualizes spatial entities (spatial entity) defined by points, lines, and surfaces, which are composed of five properties: position, shape, attribute, function, and time, with two relations: topology and order (Yan 2003, pp. 26). This section will discuss the visualization of spatial data represented by point, line, and surface events, respectively.

13.1.2.4 Point Event(s)

A representative example of point visualization is John Snow's cholera map, commonly used in epidemiology to display the location of disease outbreaks and the like. This is the first example of spatial analysis in epidemiology and has contributed greatly to the development of spatial analysis in epidemiological

research. In addition to the visualization of the point of occurrence of an event, there are also methods to represent the point of occurrence of an event and the magnitude of the event in terms of points and their magnitudes. For example, research has been conducted on a visualization method called the circle area cartogram, which represents the population distribution in each area by the location and size of circles (Dykes 1998, Inoue and Shimizu 2005, Dykes 2005, etc.). In recent years, the sophistication and generalization of Global Positioning System (GPS) technology have made it possible to record events at various points, and many studies have been conducted on this most primitive spatial visualization method.

13.1.2.5 Linear Event(line)

Next, visualization of linear events is generally used to represent linear elements in space, such as streets and roads, and to visualize the trajectory of an object's movement. Various navigation tools are a typical example of line data visualization that indicates the optimal route from a starting point to a destination based on the input of time required, distance, and other objectives.

Some methods do not preserve actual locations in real space but visualize their topological relationships. For example, many methods use multidimensional scaling (MDS) and graph theory to visualize the relationships among various locations and data by connecting them with lines (Rodger 2005; Robert 2005, etc.).

The axial map, a part of the space syntax originated by Hillier and Hanson (1984), visualizes the spatial connectivity and accessibility of urban space by dividing the street space into line segments. This is an effective visualization method (Kigawa and Furuyama 2004; Kigawa and Furuyama 2005; Kigawa and Furuyama 2006, etc.).

13.1.2.6 Surface

There are two main types of surface data: those expressed in terms of administrative boundaries such as prefecture, municipality, town, street, etc. Many census and statistical survey data are obtained in this way. In many cases, census and statistical survey data are obtained using this method, and each parcel is assigned a value. For example, a choropleth map is commonly used to visualize population data obtained from a census, in which differences in hue, saturation, and lightness of colors represent values. However, there is not necessarily a relationship between the importance of the value to be displayed and the size of the area of each compartment surrounded by administrative boundaries, etc. For example, when a small value is assigned to a large compartment, the overall distribution of the value appears to be small, which greatly affects the appearance of the information. To eliminate such differences as much as possible, there are many studies on the cartogram method, which expresses each value by the size of the area of each parcel while preserving

the spatial positional relationship and the topological shape of each parcel (Inoue and Shimizu 2005, etc.).

In addition, many studies have been conducted using methods that capture events continuously by smoothing point densities and other data using kernel functions. This operation aggregates what cannot be captured by displaying point data alone as a surface. This method is particularly effective for spatiotemporal data and other analyses in which the volume of data is necessarily large (e.g., Sadahiro 2007).

13.1.2.7 High-dimensional Spatial Data and Spatial Visualization

Information has become more abundant in recent years due to advanced information technology, and spatial data is no exception. Therefore, it has become necessary to handle various attributes and variables and their time-series changes simultaneously. Numerous visualization methods have been developed for this purpose. For example, animation methods have been recognized for their importance in visualization research and cartography (Dorling 1992; DiBiase et al. 1992 etc.). As a concrete example, animation is becoming popular as a method to grasp the aspect of change and transition by displaying the numerical change of each position at multiple points in time in a time-series frame-by-frame manner, even if it is not a dynamic object (Inoue et al. 2009, etc.).

With the recent development of remote sensing, GPS, and laser measurement technology in airplanes, wide-area and high-resolution data have become available. This has made it possible to visualize high-resolution 3D urban models (e.g., Yoshikawa 2007a, b). In addition, visualization methods that apply 3D computer graphics and virtual reality technology have become versatile and effective tools for consensus building in urban planning and landscape evaluation (e.g., Amin 2007; Yoshikawa 2007a, b etc.). The methods for capturing physical space have been rapidly improving with the progress of information and computer technology.

On the other hand, research is also being conducted on what is visible but difficult to capture due to the layering and complexity of events. In the aforementioned research related to space syntax, visual simulation methods that consider environmental indicators such as pedestrian distribution, light, wind, and atmospheric flow have been proposed and developed into tools (Takamatsu 2007, Batty 2003 etc.). The method has been used in architectural and urban design (Takamatsu 2007).

As described above, research on visualization has been conducted in various fields, and many of the visualization methods have been developed independently by practitioners and researchers, depending on the events they wish to capture and the attributes and variables they wish to display. The widespread use of GIS has made it easy to analyze data and display the results using a certain set of tools, enabling the capture of a wide range of events. Various general-purpose tools have also been developed by groups such as the GeoVISTA Center at Pennsylvania State University and the Center for Advanced Spatial Analysis (CASA) at University College London. However, both the quality and quantity of spatial data are limited. However, both the quality and quantity of spatial data are increasing daily, and there

is still room for further development of visualization methods due to the diversity and complexity of the data, as well as the complexity of spatial events caused by changes in social conditions.

In light of the above, this study proposes a method for analyzing and visualizing representative spatial data for various events in urban commercial areas, which are the most active in urban space. We focus on visualizing invisible events, latent patterns of events that conventional methods cannot grasp, and the visualization of complex and irregularly changing events.

13.2 Analytical Method and Visualization of the Direction of Commercial Concentration Expansion

13.2.1 Introduction

Commercial facilities are an essential part of urban life, and changes in these facilities always have some impact on neighborhood residents. For example, changes such as unexpected store closures in neighborhood shopping areas can disrupt the traditional shopping environment of residents. For the elderly, the commercial facilities they use daily should be located within a short distance from their residences, and this burden may be even greater. While the opening of popular brand-name stores is expected to attract many users and revitalize the surrounding area, there is also concern that the large influx of visitors may cause congestion and other problems that could adversely affect the living environment of residents in the surrounding area. Changes such as the opening and closing of commercial facilities are always occurring in commercial clusters. While such changes can be good for revitalizing the area, they can also significantly impact residents, such as the deterioration of the surrounding residential environment and the decline of the surrounding area due to unjustified development, etc. Therefore, in urban planning and development, it is important to grasp the changes and trends to control them appropriately and accurately. It is necessary to accurately grasp the changes and trends to control them appropriately in urban planning and development.

In light of the above, this chapter focuses on the formation process of commercial clusters in urban areas. It proposes a method for describing, analyzing, and visualizing the trends of changes in these clusters. Section 13.2 proposes a method for describing and analyzing the direction in which commercial clusters expand based on the time when each store in a commercial cluster opens. Section 13.4 describes, analyzes, visualizes, and discusses the results using data from Shibuya Ward, Tokyo, as an empirical analysis to verify the effectiveness of the proposed method. Finally, Section 13.4 summarizes the chapter and discusses future issues.

This chapter was added based on the content of “Analysis Method and Visualization of the Direction of Commercial Agglomeration Expansion” (Inasaka and Sadahiro 2010), which was accepted as a research paper in the Transactions of the Architectural Institute of Japan, Planning Division.

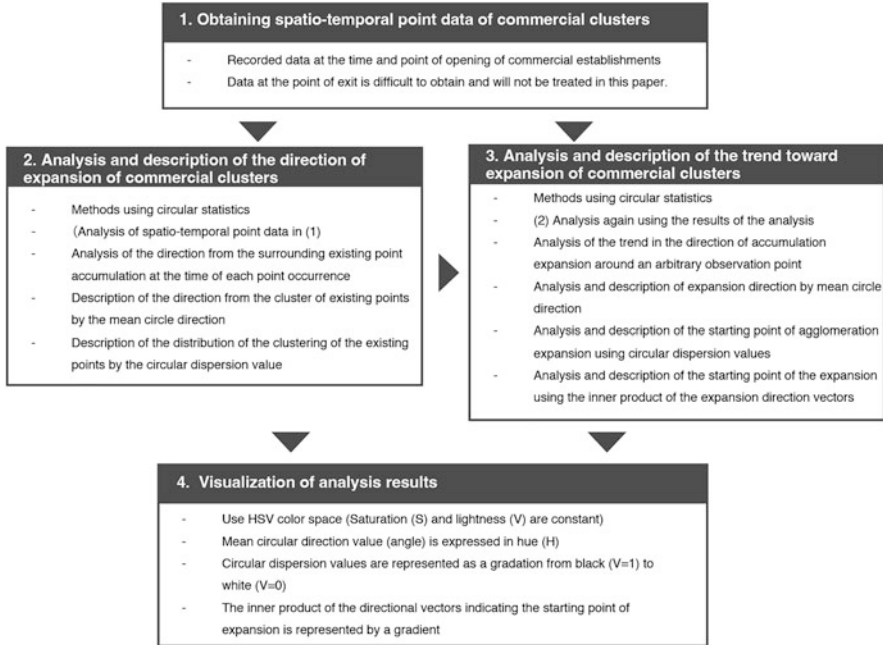


Fig. 13.1 The flow of this section

13.2.2 Analytical Method for Describing the Direction of Expansion of Commercial Clusters

13.2.2.1 Analysis and Description of the Direction of Commercial Agglomeration Expansion Using Spatiotemporal Point Data

Assume that we have spatiotemporal data on existing commercial establishments in a certain region. The location of each commercial facility is represented as a point, and the time when each store opened is recorded. Note that we do not include closed commercial establishments in our analysis since it is often difficult to obtain such information. However, in the “Survey of Establishments and Businesses,”¹ the number of closed and newly opened establishments is almost the same for commercial establishments related to retail, restaurants, and services. New establishments may open in the same location after closing. Therefore, it should be noted that it is necessary to consider the re-filling of commercial clusters, such as new store openings after store closures. In this chapter, we define this data as commercial clusters (Fig. 13.1).

¹ (Note 1) See Statistical Survey of Business Establishments and Enterprises 2004 (Tokyo Metropolitan Government, Table 20, Shibuya Ward). (<http://www.stat.go.jp/data/jigyuu/2004/>)

Next, we propose a method for describing the direction in which commercial clusters expand during their formation process. For the above commercial clusters, we analyze in which direction the individual stores have expanded while joining the existing commercial clusters when they opened new stores. We use the circular statistical method² while tracing the past formation process.

From this data, we first determine the current commercial agglomeration. We define a commercial cluster as a set consisting of all stores.

Let us assume that the commercial facilities that comprise the existing commercial clusters are s_1, s_2, \dots, s_n . These facilities are located in the order of s_1 , and the aggregate $S = \{s_1, s_2, \dots, s_n\}$ constitute the current commercial agglomeration.

Next, a circular data is created that describes a certain direction of existing stores in the vicinity, centered on each store to be analyzed. The state of the commercial clusters at each of the intermediate points in time p can be determined by the following equation. s_p the set of existing commercial stores at the point in time when $S_{p-1} = \{s_1, s_2, \dots, s_{p-1}\}$. The set of points s_p and the set S_{p-1} and the unit vector formed by the points constituting the set $L_p = \{l_1, l_2, \dots, l_{p-1}\}$ and the angle formed concerning the east on the map is $\Theta_p = \{\theta_1, \theta_2, \dots, \theta_{p-1}\}$ and the angle formed concerning the east on the map is defined as Here, we assume that s_p on the unit circle centered at Θ_p is defined as the circle data. In this paper, unless otherwise noted, the angles are measured in radian with the east direction set to 0 (rad). This data uses the following equation Θ_p for the mean circular direction $\bar{\theta}$ (Fisher 1993; Brunson and Corcoran 2006; Corcoran et al. 2007).

$$C = \sum_i^{p-1} \cos \theta_i, S = \sum_i^{p-1} \sin \theta_i, R^2 = C^2 + S^2 (R \geq 0) \quad (13.1)$$

The mean circular direction $\bar{\theta}$ is a composite vector of a set of unit vectors $L_p = \{l_1, l_2, \dots, l_{p-1}\}$, and its angle is given by using the value obtained in Eq. (13.1) according to the following:

$$\bar{\theta} = \begin{cases} \tan^{-1} \left(\frac{S}{C} \right) & S > 0, C > 0 \\ \tan^{-1} \left(\frac{S}{C} \right) + \pi & C < 0 \\ \tan^{-1} \left(\frac{S}{C} \right) + 2\pi & S < 0, C > 0 \end{cases} \quad (13.2)$$

R is the composite length of its composite vector, which lies in the range $[0, p-1]$. \bar{R} represents average composite length as follow

$$\bar{R} = R / (p - 1) \quad (13.3)$$

² (Note 2) Sometimes referred to as directional statistics This method has recently been attracting attention in computational statistics, such as Shimizu (2008)

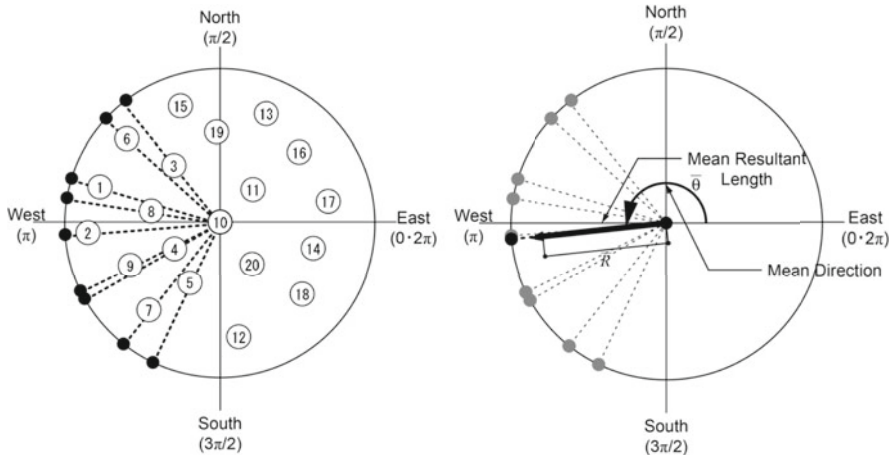
and are positioned in the range $[0, 1]$. \bar{R} the maximum and minimum values of $\bar{R} = 1$, indicating that all point data are matched. However, for the average composite length $\bar{R} = 0$ is the case for the average composite length $n(n \geq 3)$. It should be noted, however, that in the case of the average composite length, in addition to the case where the points are evenly distributed in many directions to divide the circumference equally, there is another case where the points are distributed in a straight line up through the center of the unit circle to bisect the circumference.

$$V = 1 - \bar{R} \quad (13.4)$$

V is defined as the circular variance (Note 5). As with the variance of linear data, the smaller the value of the circular variance, the more concentrated the data distribution. The circular variance $V = 1$ property is similar to the above property of the mean composite length $\bar{R} = 0$. Similarly to the above property of the mean composite length, the property of $n(n \geq 3)$ In addition to the case where the point sequences are evenly distributed in many directions to divide the circumference into two equal parts, there is also the case where the point sequences are distributed in the direction above the straight line passing through the center of the unit circle to divide the circumference into two equal parts. However, the cases in which the point sequences are uniformly distributed in multiple directions and the case in which they are distributed in a straight line correspond to the cases in which the accumulation expands in multiple directions around a certain base facility and the case in which it expands in a straight line along a main road, respectively, in urban space, and their meanings are quite different. In the above two cases, it cannot be interpreted that the distribution is uniformly distributed so that the dispersion value is 0 in the linear case. With the above properties in mind, $V < 1$ is considered in this method.

We propose a method for describing the direction of expansion of commercial agglomeration using the above circular statistics method. In this paper, this method is called the “expanded direction description method.” The calculation procedure is as follows.

First, the spatiotemporal data of the existing commercial facilities $i(0 < i < t)$ at the point in time $[0, t]$ of the existing commercial facility. p_i The first step is to consider a point that occurred at time $[0, t]$. The point p_i as the base point, and the points that occurred before the point $i(0 < i < t)$. The points that occurred before the point in time $\{p_0, p_1, p_2, \dots, p_{i-1}\}$ and plot the intersection of the points on the unit circle on the circumference of the circle. The angles formed by the unit vectors connecting the points plotted on the unit circle and the base point p_i . The angle formed by the unit vector connecting the points plotted on the unit circle and the base point is used in Eqs. (13.1) and (13.2) to obtain the average circle direction $\bar{\theta}$. The obtained mean circle direction is calculated using Eqs. (13.1) and (13.2). The



- Flow up to the description of the direction using the circular statistical method
- (1) The numbers in the circle indicate the order in which the points occur.
 - (2) In the left figure, the 10th generated point is the base point and connects it with a point that occurred in the past. Plot on the unit circle.
 - (3) A line connecting a point plotted on the unit circle and the base point. The angle formed by the average circle direction using the circular statistics method. The following equation is obtained.
 - (4) Invert the obtained result by $-\pi$ and calculate the existing accumulation or the direction of expansion is the direction of expansion of the
 - (5) Also, the average of each unit vector in (3) is the average composite vector.

Fig. 13.2 Concept of circular statistics relationship between mean circular direction and circular variance

obtained average circle direction $\bar{\theta}$ by the following equation π . The obtained mean circle direction is inverted by (Note 5). Circular variance is a translation of circular variance.

$$d = \begin{cases} \bar{\theta} + \pi & (0 < \bar{\theta} \leq \pi) \\ \bar{\theta} - \pi & (\pi < \bar{\theta} \leq 2\pi) \end{cases}, \quad (0 < d \leq 2\pi) \tag{13.5}$$

Next, the length of the composite vector of each unit vector and the number of points i generated up to that point are substituted into Eq. (13.3) to obtain the average composite length, which is then substituted into Eq. (13.4) to obtain the circle variance V (Fig. 13.2).

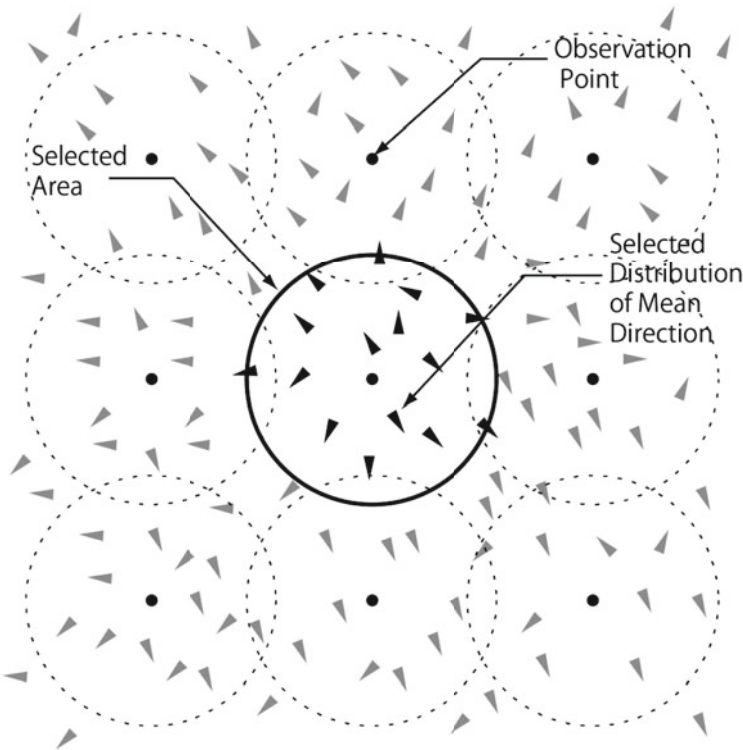
13.2.2.2 Analysis and Description of Trends in the Direction of Expansion of Commercial Clusters

Using the results of the expansion direction of each spatiotemporal point obtained through the above expansion direction description method, we analyze the trend

of the expansion direction of accumulation at an arbitrary observation point. This paper calls this method the “expansion direction trend description method.” The calculation procedure is as follows.

First, assume that there is a spatiotemporal point distribution that includes the magnification direction of each point calculated from the spatiotemporal data of existing commercial facilities at the obtained time using the magnification direction description method proposed earlier. Then, we generate uniform observation points at arbitrary distance intervals on the spatiotemporal point distribution. Generate a unit circle with an arbitrary radius centered on an observation point, and extract the spatiotemporal points encompassed by the circle. The unit circle defines the direction of expansion of each point.

Plot the result on a plot of the mean circle direction. The average circle direction is obtained using Eqs. (13.1) and (13.2). Substitute the length of the composite vector formed by the center of the unit circle and the expansion direction of each point plotted on the circumference of the unit circle and the number of space-time points included in Eq. (13.3) to obtain the average composite length, which is then



The observation points are generated at arbitrary intervals and encompassed within a buffer range of arbitrary radius. The average direction of each above point is tabulated using circular statistical techniques.

Fig. 13.3 Description of expansion direction trend from an arbitrary observation point

substituted into Eq. (13.4) to obtain the circle variance value (Fig. 13.3). In this case, the observation points generated at arbitrary distance intervals will appear as differences in the resolution of the visualization when the analysis results are displayed, depending on the differences in the intervals. The radius of the circle used to select the spatiotemporal point data around the observation point is the scale that this analysis can read.

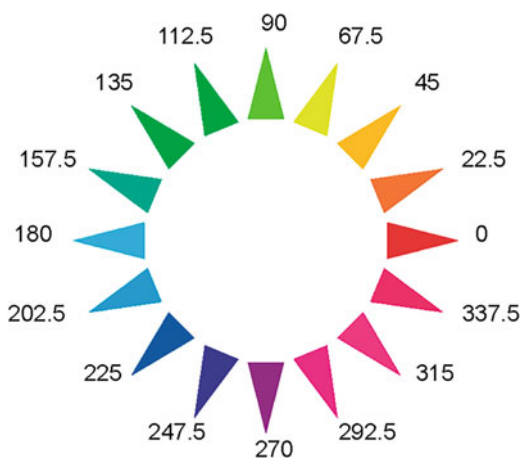
The average circle direction obtained here indicates the trend of the expansion direction of the accumulation concerning each observation point. If the circle dispersion is close to 0, the directionality is strongly in the direction of the obtained mean circle. If it is close to 1, the expansion is almost uniform in all directions.

13.2.2.3 Visualization of Analysis Results Using HSV Color Space

The values calculated by the above-mentioned expansion direction description method and the expansion direction trend description method are visualized as follows. The direction of expansion description method calculates the direction of expansion for each spatiotemporal point and the direction of expansion and circular dispersion values obtained. The direction of magnification was calculated for each point by describing the trend of magnification direction, and the mean circle direction and circle variance were obtained. Then, the magnification direction, mean circle direction, and circle dispersion are visualized on a map.

The direction of the mean circle is visualized using ArcGIS 9.3, with the east direction set to 0 (rad) and the angles indicated by the arrows. The HSV color space is defined by hue (H: hue), saturation (S: saturation), and value (V: value) and is suitable for representing the angles of the analysis results. The circular dispersion is visualized by a white-to-black gradient from a dispersion value of 0 to 1 (Fig. 13.4).

Fig. 13.4 Visualization of mean circle direction using HSV color space. Classify and assign observed angles within ± 11.25 degrees



13.2.2.4 A Method for Visualizing the Starting Point of Commercial Agglomeration Expansion Using Vector Analysis

Using directional data describing the angle of expansion of each store in a commercial cluster, we propose a method of searching for the starting point of the expansion of the commercial cluster by applying the method of vector analysis. The computational procedure is as follows.

From the previous method, for a set of commercial stores SH for each store in the commercial agglomeration to which they belong, a set of vectors $\vec{P}_n = \{\vec{p}_1, \vec{p}_2, \dots, \vec{p}_n\}$ and for a store \vec{p} for a store in the set, as defined by the vector (x, y) for a store in the set. The data are assumed to be arranged in ascending order by the time of the source.

Vector of stores opened at a given point in time i and the vector of commercial stores that have already opened at a given point in time \vec{p}_i and the set of vectors of commercial stores that have already opened in the surrounding area is defined by $\vec{P}_{i-1} = \{\vec{p}_1, \vec{p}_2, \dots, \vec{p}_{i-1}\}$ where the vectors \vec{p}_i and the vector $\vec{p}_o \in \vec{P}_{i-1}$ the inner product of these two vectors can be calculated using Eq. (13.5) below, and $\cos\theta$ is obtained by Eq. (13.6).

$$\vec{p}_o = (x_o, y_o), \quad \vec{p}_i = (x_i, y_i) \text{ then the}$$

$$\vec{p}_o \bullet \vec{p}_i = x_o x_i + y_o y_i = |p_o| |p_i| \cos \theta \quad (13.5)$$

$$\cos \theta = \frac{\vec{p}_o \bullet \vec{p}_i}{|p_o| |p_i|} = \frac{x_o x_i + y_o y_i}{\sqrt{x_o^2 + y_o^2} \sqrt{x_i^2 + y_i^2}} \quad (13.6)$$

From the above calculations, it can be seen that the vectors \vec{p}_i and the set \vec{P}_{i-1} for all vectors in the set $\cos\theta$ values are obtained for all vectors of using the results, the shape of the distribution of vectors indicating the direction of origin of the expansion of commercial concentration at the location of the store p_i . The following Eq. (13.7) gives the shape of the distribution of vectors that indicate the direction of origin of the expansion of commercial clusters at the location of a store.

$$C_i = \frac{\sum_{k=1}^{i-1} \cos \theta_k}{i-1} \quad (13.7)$$

C_i takes values in the range $[-1, 1]$. Around 1, there is a concentration of the vector distribution, and around -1 , there is a divergence of the vector distribution. Furthermore, a random situation is observed near 0. In other words, when the value of C_i around 1 indicates that the area is near the starting point of the expansion of commercial accumulation, while the area around -1 indicates that the area is at the boundary of the expansion.

Using the above method, the values of each store belonging to a commercial cluster are visualized on a map by painting them with a gradient. C_i the above

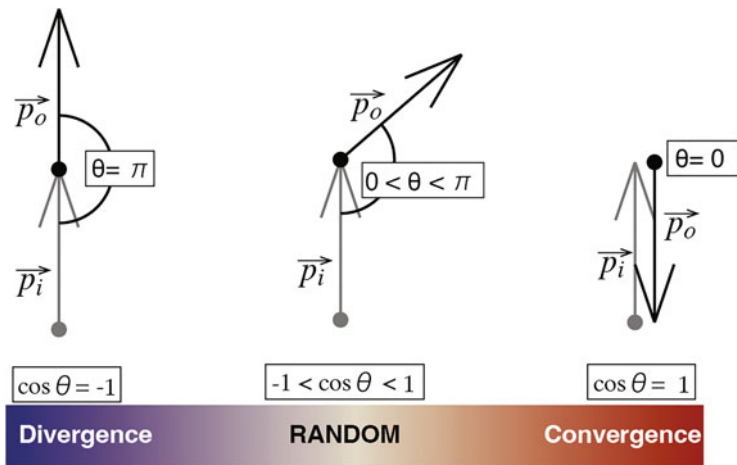


Fig. 13.5 $\cos \theta$ obtained from the inner product of vectors θ values and directional patterns obtained from the inner product of vectors

method is used to visualize the value of each store belonging to a commercial cluster by painting it in a gradation on a map and to examine the starting points of the expansion of commercial clusters, the boundaries of commercial clusters, and the scale and distribution of commercial clusters (Fig. 13.5).

13.3 Formation Process Analysis of Commercial Agglomeration in Shibuya

13.3.1 About Shibuya Ward

Shibuya Ward (Fig. 13.6) is located in the western part of Tokyo, bordered by Shinjuku and Nakano Wards to the north, Suginami, and Setagaya Wards to the west, Meguro and Shinagawa Wards to the south, and Minato Wards to the east. The area is long and narrow from north to south, with large green areas such as Yoyogi Park and Meiji Shrine in the center. The area is also home to some of Tokyo’s most prominent commercial districts, including the areas around Shibuya, Ebisu, and Harajuku stations, as well as a variety of neighborhood shopping areas along the Keio Line, surrounding residential areas, and upscale residential areas such as Shoto. In addition, it is positioned as one of Tokyo’s sub-centers, with many major railroad lines and main arterial roads intersecting the city. Therefore, it is considered a suitable site for the empirical analysis in this chapter.



Fig. 13.6 Schematic of Shibuya and Shinjuku Ward

13.3.2 About the Data Set

In this chapter, we use the address-matched “NTT Town Pages Data” for Shibuya Ward, Tokyo, from 1989 to 2007 as an example of applying the above method. This data is suitable for understanding time-series changes because it is published regularly on a yearly or, in recent years, bi-monthly basis. In this study, we use the data published in September of each fiscal year from 1989 to 1994 and published every other month in January, March, May, July, September, and November from 1995 to 2007. A total of 178,859 stores are included in the analysis. The stores covered here appear in the retail, restaurant, and service industries in the NTT Town Pages Data.

The data used in this study is based on the date when each store was first listed on the website, either annually or bi-monthly, and the store is assumed to have

opened at that time. However, the data do not show the detailed time of each store opening for each fiscal year or each bi-monthly period. In other words, the order in which stores were opened during each fiscal year or bi-monthly period is unclear. Therefore, in this paper, we assume that multiple store openings at each point in time occurred at the same time.

Since the relationship between stores close to each other is stronger than between stores as far away as possible, the analysis is based on the relationship between stores included within an arbitrary radius of a circle centered on each store to be analyzed.

13.3.3 Analysis of the Direction of Agglomeration Expansion as Seen in the Spatiotemporal Point Data and Discussion of Examples of the Application of Visualization

The method proposed in this chapter makes it difficult to determine its radius during the analysis uniquely. However, since the results depend on the radius distance, this paper analyzes data within a circle of radius 1000 m, 750 m, 500 m, 250 m, 100 m, 50 m, and 30 m, with each store as the base point. The results are as follows. We first discuss the analysis results for the circles with radii of 1000 m, 500 m, and 250 m, where the results are more pronounced.

In this chapter, considering the ease of viewing the analysis results, the angles indicating the direction were divided into 16 azimuths from 0 to 360 degrees, and the observed mean circle angles were classified and visualized for each 22.5-degree width range centered on each angle. The circular dispersion values were expressed as a 10-step gradation.

First, in the analysis of the 1000 m radius buffer (Fig. 13.7), we can observe arrows extending outward from the major railroad stations in Shibuya Ward, namely Shibuya, Ebisu, Yoyogi, and Shinjuku stations. From this, it can be inferred that the stations serve as the base points for the expansion of commercial clusters. Next, focusing on the locations estimated to be the base points of each expansion, we can see that the distribution is not uniform, with large and small distributions in each angular zone. For example, when we focus on the expansion based on the area around Shibuya Station, we observe that the distribution of arrows in the northeast direction is significantly smaller than those in other directions. This indicates that the directionality of expansion in that direction is strong. This is consistent with the location of Meiji-dori Avenue, which suggests that commercial clusters are expanding from Shibuya Station to Harajuku. Similarly, the distribution of arrows along the Keio Line and Koshu Kaido that extend westward from Shinjuku Station is also strongly oriented, suggesting that commercial clusters are expanding westward from the base point of Shinjuku Station.

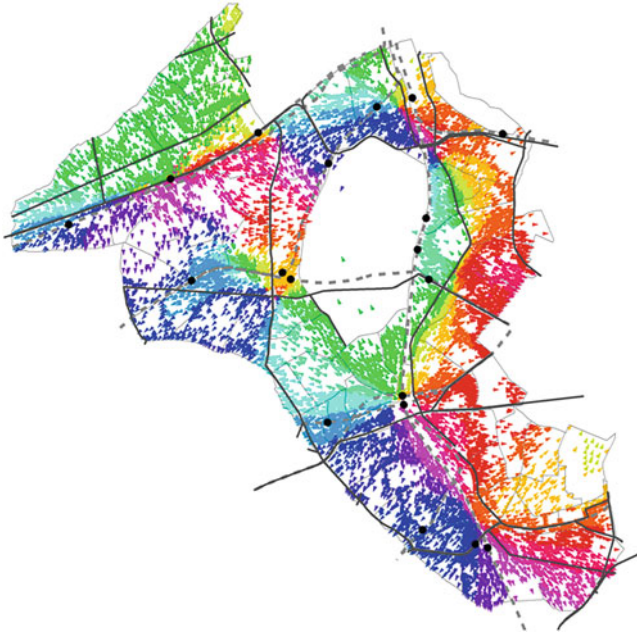


Fig. 13.7 Distribution of expanding direction at 1000 m buffer

In addition, in the circular dispersion distribution chart (Fig. 13.8), we can see results consistent with the above discussion of locations that serve as the base points for expansion. It can be seen that the locations with high circular dispersion are distributed around the major stations of Shibuya, Ebisu, Yoyogi, and Shinjuku. This indicates that relatively old stores are uniformly distributed near the commercial clusters, which is the base point for expanding the commercial clusters, as discussed in the expansion direction distribution map. Similarly, along the main roads, Meiji-dori and Koshu kaido, the locations with high circle dispersion are distributed in a long and thin line, and the commercial clusters are extended outward in parallel with these streets.

In the 500-m buffer (Fig. 13.9), as in the 1000-m buffer, in addition to the extensions centered on major stations, the distribution of arrows in the direction of extensions based on relatively small stations, such as Hatsudai, Hatagaya, and Sasazuka stations on the Keio Line and Yoyogi Uehara station on the Odakyu Line, which was not observed when the buffer radius was large, can be observed. The distribution of arrows in the direction of the road can be observed. We can also observe locations where opposite arrows collide along roads. This is caused by the collision of expansion based on each station and can be assumed to be the boundary line between each expanding commercial cluster.

As in the 1000 m buffer analysis, the circular dispersion distribution (Fig. 13.10) is also higher at the locations that can be inferred as the base points of the

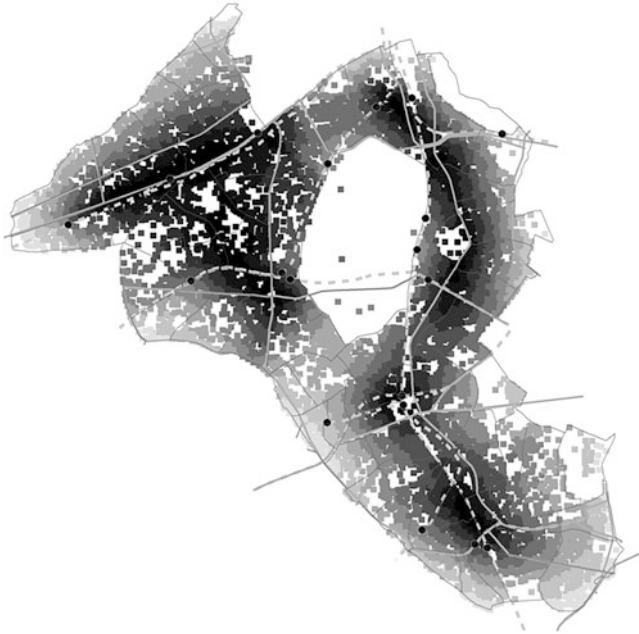


Fig. 13.8 Circular dispersion distribution at 1000 m buffer

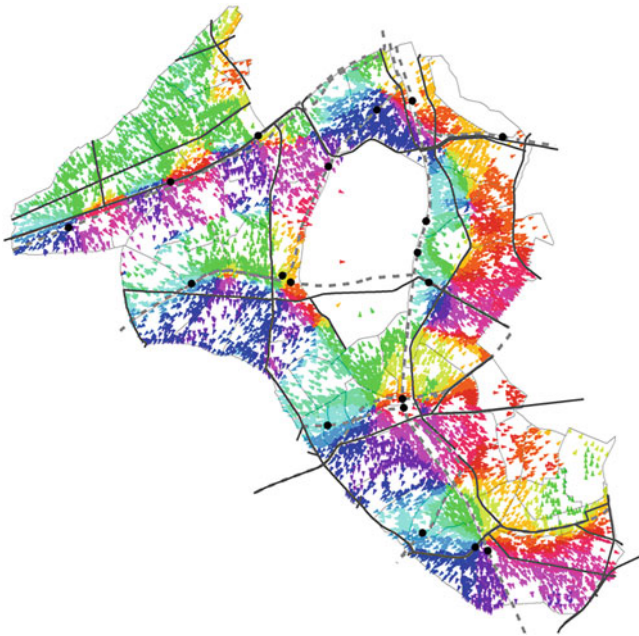


Fig. 13.9 Distribution of expanding direction at 500 m buffer



Fig. 13.10 Circular dispersion distribution at 500 m buffer

expansion by visualization of the mean circular direction. In addition, the circular dispersion is high at the locations where arrows pointing in opposite directions collide, which can be inferred as the locations where the expansion collides with the commercial accumulation. In addition, although not shown in the expansion direction distribution map, the Hiroo area on the east side of Ebisu station has a high dispersion value. Although there is no station or other base point, it is considered the base point of the expansion of the area in light of the other trends shown in the circular dispersion.

In the 250-m buffer (Fig. 13.11), we observed more detailed changes than in the analysis using a larger buffer radius. The arrow distribution in the direction of expansion is not observed in the above analysis. Still, it is based on the relatively small station area that does not face an arterial road, such as the Daikanyama station. The arrow distribution along arterial roads also shows a more localized change in the arrow distribution along roads, showing a strong expansion directionality in the analysis results for the large buffer radius. In light of the previous discussion, it can be inferred that the central facility within the smaller regional unit is located at the base of this change. As an example of this being particularly evident, we observed the distribution of arrows extending northward from Hatagaya and Sasazuka stations along the Keio Line. We captured relatively small changes, such as in neighborhood shopping areas.

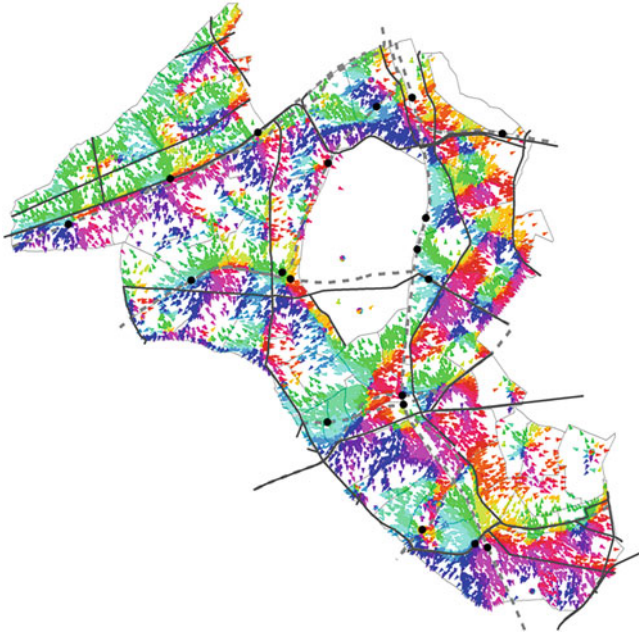


Fig. 13.11 Distribution of expanding direction at 250 m buffer

Similarly, the circular dispersion distribution map (Fig. 13.12) captures minute changes in commercial clusters, which were not observed when analyzing large buffer radii. As mentioned earlier, relatively high circular dispersion is observed for large and small railroad stations and arterial roads. At the same time, high values are also observed for locations where arrows pointing in opposite directions collide. In other words, the locations with high circular dispersion are related to the cases where they are the base points of the expansion of commercial clusters, and the boundary areas where the expansion of commercial clusters collides with each other and where a straight road passes between the clusters and stores are located on the line of the road. It corresponds to the case where the base point is on a straight line with the point sequence bisecting the circumference, which is a property of circular dispersion in this method.

It can be observed that the smaller the buffer radius, the more detailed the analysis results. By decreasing the buffer radius, more detailed changes that were not apparent when the analysis target was selected with a large radius can be captured, such as changes in small stations and areas with characteristics as a region but no facilities that can serve as a base point. On the other hand, if the buffer radius is too small, such as 50 m or 30 m, the arrows will be arranged irregularly, and no trend can be read. This is considered to be a limitation of this method.



Fig. 13.12 Circular dispersion distribution at 250 m buffer

13.3.4 Analysis of the Trend in the Direction of Agglomeration Expansion and Discussion of Examples of Application of Visualization

Based on the results of the previous analysis, we analyze the trend in the direction of expansion at arbitrary observation points. In this paper, the analysis was conducted using a grid of observation points at intervals of 100 m. The observation area centered on an observation point is affected by the circle's radius encompassing the observation target. The radii of the circles were 1000 m, 750 m, 500 m, 250 m, and 100 m, and the spatiotemporal point data were tabulated for each of these radii. The above analysis found that the 500 m buffer radius captured the relatively wide changes based on major stations and the relatively narrow changes based on arterial roads and small- and medium-scale stations, respectively. The results of this analysis were used to examine the trend in the direction of expansion within the radii of 500 m and 250 m, where the differences in the results from the previously defined observation points were pronounced. The same method was used for the visualization of the results.

As shown in Fig. 13.13, the distribution of arrows indicating the direction of expansion of the concentration is observed near Shibuya and Ebisu stations, which are the main stations in this area, and near the intersection of Meiji-Dori and

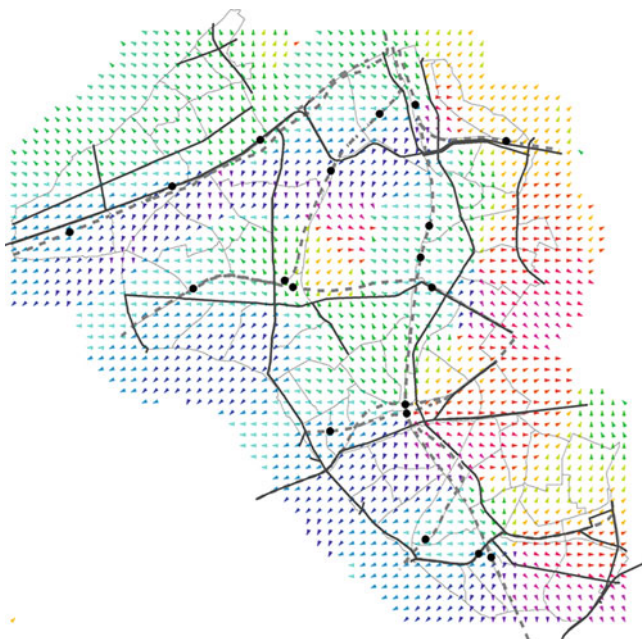


Fig. 13.13 500 m buffer result use of the distribution in the direction of expansion 500 m at buffer Enlarged directional trend distribution

Omotesando, which are the main roads in this area. The same directional arrows can also be observed along Koshu Kaido in a uniform westerly direction, suggesting that the concentration tends to expand along the main road.

The results of this analysis (Fig. 13.14) show that the dispersion values are high near the major stations and trunk roads mentioned above, and these areas can be positioned as the base points for the expansion trend. In particular, the areas with high circular dispersion near trunk roads are long and narrow, indicating that roads are the standard for expansion.

(Expanding trend within a buffer radius of 250 m from the observation point) A more detailed change trend can be read when the observation buffer radius from the observation point in Fig. 13.15 is reduced. In addition to the trends based on major stations and intersections with main roads, small-scale expansion trends can be observed based on stations with residential areas around them, such as Hatsudai, Hatagaya, and Sasazuka stations on the Keio Line and Yoyogi Uehara station on the Odakyu Line. The areas with large values in the circular distribution map (Fig. 13.16) are concentrated near the aforementioned points, and by comparing them with the map showing the trend in the direction of expansion, it can be seen that they are the base points for the expansion of the agglomeration.

(Analysis results for other buffers and overall discussion) Similar to the discussion in the previous Sect. 13.3.3, it can be observed that the analysis results become

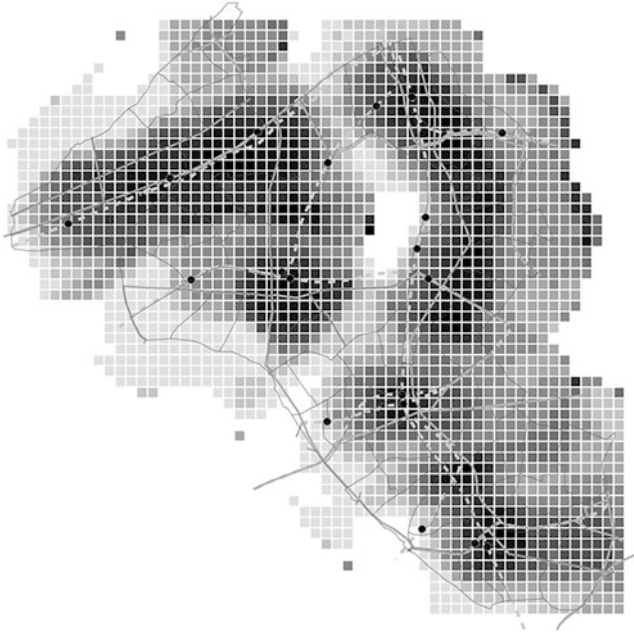


Fig. 13.14 500 m buffer results use of 500 m distribution in the direction of expansion 500 m buffer time Circular dispersion distribution

more detailed as the buffer radius becomes smaller, depending on the size of the buffer radius that determines the area to be analyzed. For the extended directional distribution map results with an irregular array of arrows, such as the results with a buffer radius of 50 m or 30 m, no significant trend can be read in both the extended directional trend distribution map and its circular dispersion distribution map. This is considered to be a limitation of this method.

13.3.5 Analysis and Discussion Using Commercial Agglomeration Expansion Origin Direction Data (Figs. 13.17 and 13.18)

Figures 13.4 and 13.7 show that vectors indicating the direction of origin are concentrated around major stations such as Shinjuku, Shibuya, and Takadanobaba Stations. The 500 m buffer in Fig. 13.7 shows that the vectors are concentrated around Hatsudai, Hatagaya, and Sasazuka stations along the Keio Line, around Kagurazaka, and near the intersection of Meiji-Dori and Omotesando, where many visitors come without depending on nearby shopping areas or major stations.



Fig. 13.15 500 m buffer result use of the distribution in the direction of expansion 250 m at buffer
Enlarged directional trend distribution

13.3.6 Visualization of 500 m Buffer Accumulation Expansion Starting Point (Figs. 13.19 and 13.20)

As explained above, the areas around the major stations are painted in red, indicating the starting points of the expansion of commercial clusters. In addition, some locations far from the main station are also indicated as the starting points, indicating that the neighborhood shopping areas and places frequented by many visitors also indicate the starting points of commercial cluster expansion.

Many of the points painted in blue are located between multiple origins, indicating locations where the expansion between each commercial agglomeration converges.

13.3.7 Visualization of 250 m Buffer Accumulation Expansion Starting Point (Figs. 13.21 and 13.22)

Next, when the buffer is set to 250 m to visualize the starting point of the expansion of commercial clusters, the results are almost the same as when the data is aggregated at 500 m. However, when we look at the area around major stations

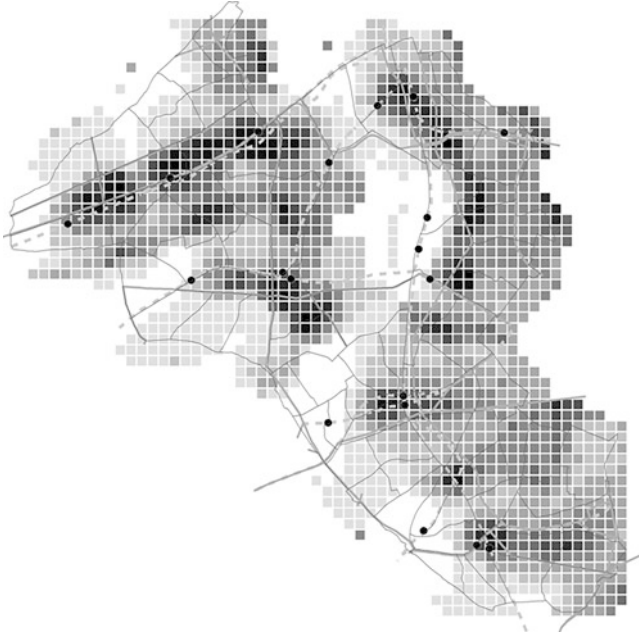


Fig. 13.16 500 m buffer results use of 500 m distribution in the direction of expansion 250 m at buffer Circular dispersion distribution

such as Shibuya and Shinjuku stations, we can see differences by area divided by stations and railroad lines. In other words, by aggregating the data in 250-m buffers, we can more precisely read the differences in the expansion starting points of the regions.

13.3.8 Differences in Visualization Results Depending on Buffer Size

Regarding the effect of buffer size, a relatively large area, such as 500 m, is suitable for reading a more macroscopic situation, such as an expansion centered on a major station. On the other hand, when the buffer size is smaller than 250 m, it is possible to read differences in the area bounded by regional dividing elements such as major stations and railroad tracks, and it is considered to capture more microscopic aspects of the area.

Using detailed spatiotemporal data, we proposed a method to visualize the starting point and convergence point of the expansion of commercial clusters by applying a vector analysis method to the pattern of the expansion of commercial



Fig. 13.17 Commercial agglomeration expansion starting point directional diagram (750 m buffer)

clusters. We also conducted an empirical analysis using actual data. The starting points and convergence points of the expansion were visualized.

In the future, we would like to conduct Monte Carlo simulations and perform statistical tests on the probability distributions obtained from the simulations to investigate the usefulness of this method further.



Fig. 13.18 Commercial agglomeration expansion starting point directional diagram (500 m buffer)

13.4 Conclusion

13.4.1 Summary and Future Issues

We proposed a method for describing, analyzing, and visualizing changes accompanying the expansion of complex commercial clusters using a circular statistical method, which is difficult to grasp using conventional methods such as paper maps, analysis based on ordinary statistical data, and animation-like methods that

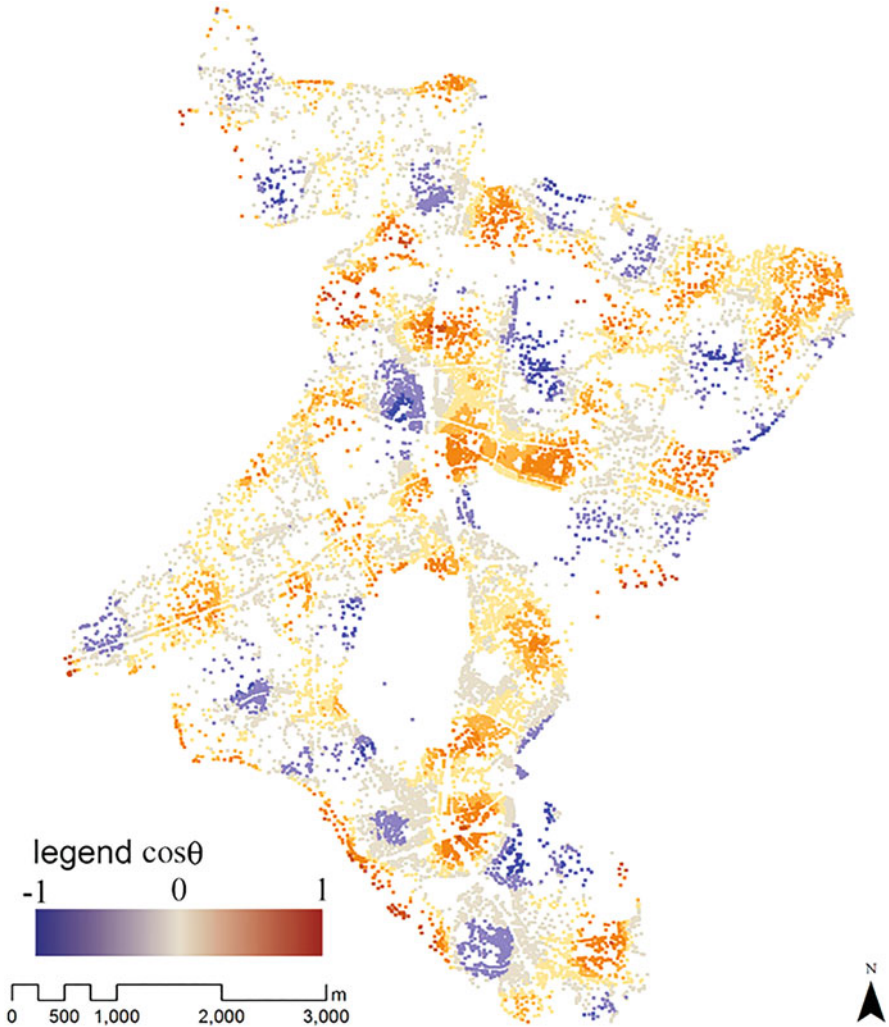


Fig. 13.19 $\cos\theta$ value distribution (at 500 m buffer) (750 m enlarged starting point directional map)

sequentially display time-series changes. The method is analyzed empirically using spatiotemporal point data of commercial stores in Shibuya Ward, Tokyo, and the results are discussed.

The results obtained are summarized below.

1. First, we analyzed the direction of expansion of commercial clusters by using the circular statistical method to analyze the direction of new store openings relative to existing clusters in each time cross-section and were able to visualize the results. The results show that the arrow points are concentrated and distributed

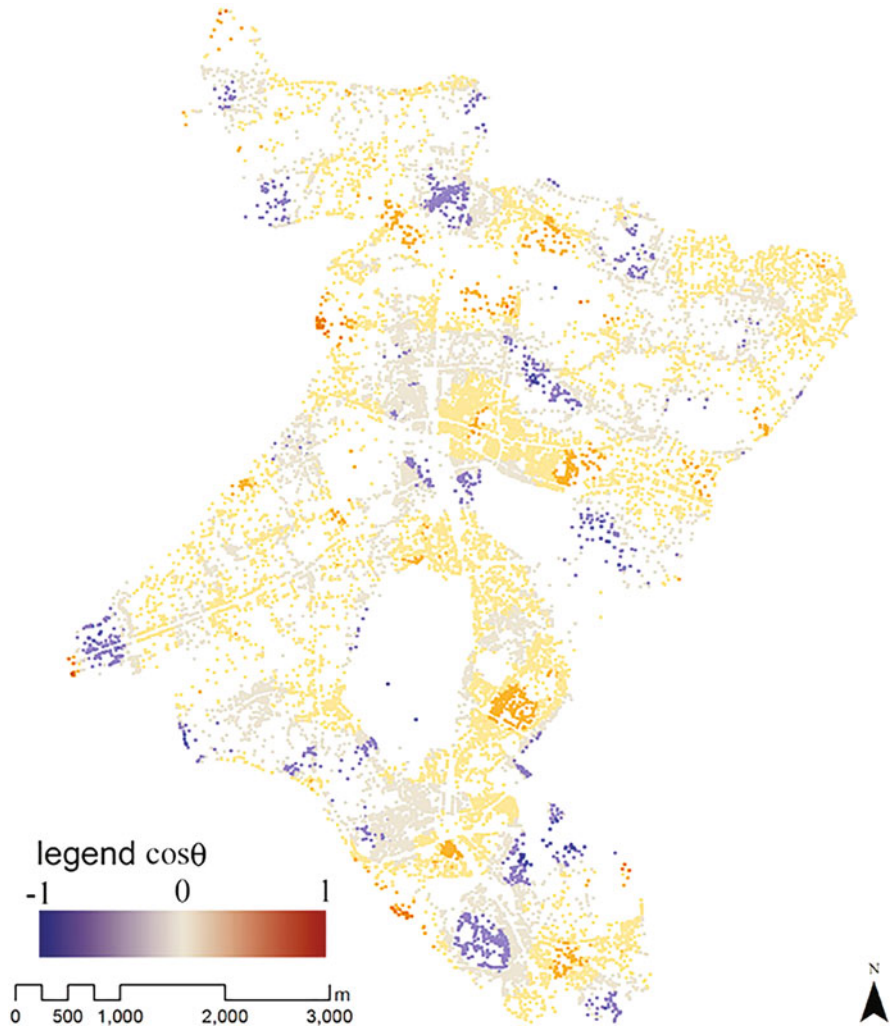


Fig. 13.20 $\cos\theta$ value distribution (at 500 m buffer) (500 m enlarged starting point directional map)

at the points that are the base points of the expansion of commercial clusters and that they are located near facilities and roads that are generally considered to be the base points of commercial cluster expansion, such as railroad stations and arterial roads, in comparison with the current situation in Shibuya Ward. While conventional mesh data analysis can provide a rough trend of expansion, the analysis using this method can be evaluated to a certain extent in that it can simultaneously identify the base points and directions of expansion.

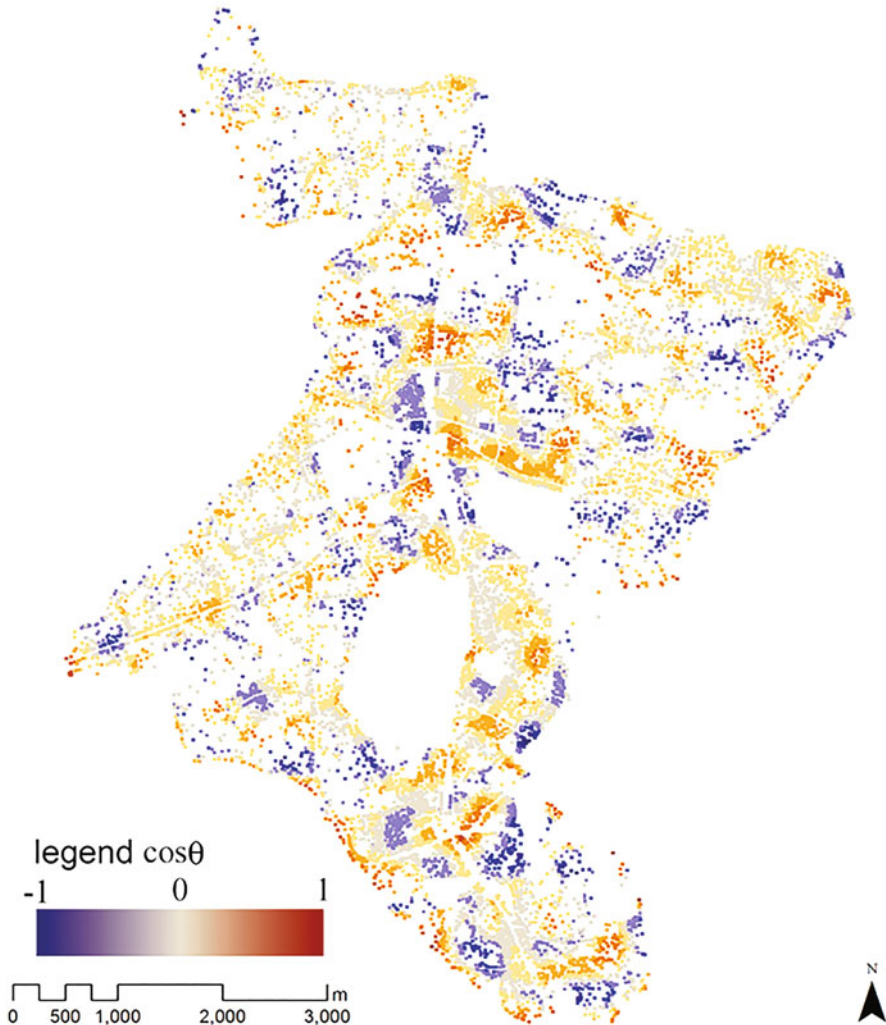


Fig. 13.21 $\cos\theta$ value distribution (at 250 m buffer) (750 m enlarged starting point directional map)

2. In the map of the distribution of circular dispersion, it was found that the circular dispersion value is decidedly high in the area that can be concluded as the base point in the above map showing the direction of expansion. In other words, high circular dispersion means that the points to be analyzed are uniformly distributed in all directions from the base point. In this case, the area is positioned where relatively old stores are concentrated. The conclusion is generally consistent that the area is the base point of commercial cluster expansion and is being extended outward from there. Although previous studies have captured changes

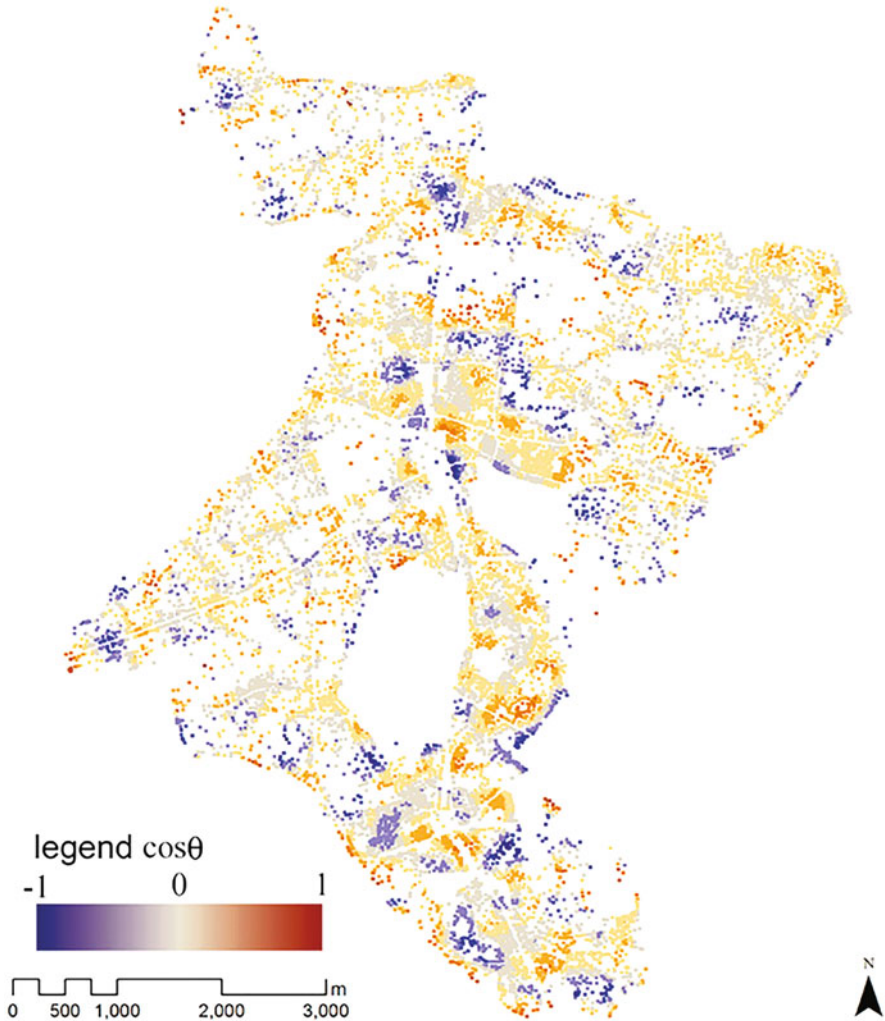


Fig. 13.22 θ value distribution (at 250 m buffer) (500 m enlarged starting point directional map)

in commercial clusters based on train stations, in reality, this method is not limited to such studies but also allows us to understand changes in areas without a clear base point, such as streets or train stations.

3. The conventional method made it difficult to analyze data at different scales, such as township units or mesh data. Still, with this method, it is possible to change the scale of analysis freely. For example, the smaller the buffer radius determining the analysis target area, the more detailed the results become. The smaller the radius, the more detailed the analysis results become. By reducing the buffer radius, we succeeded in capturing more detailed changes, such as changes

in small stations and areas with characteristics as a region but no facilities that can serve as a base point, which were not revealed when the analysis target was selected with a large radius.

4. The analysis from the equally spaced observation points enabled us to capture the expansion trend of the area around each observation point and to show each change more clearly. Similarly, the dispersion diagram showed that the high dispersion values are the points of almost uniform expansion in all directions at the observation points and are the base points of the expansion of commercial clusters.

The following three issues need to be addressed in the future.

1. To simplify the method, we use spatiotemporal data that only considers the location of stores and the time of their opening. In reality, many stores close, and their impact on the formation process is not small. To reproduce the formation process of commercial areas more faithfully, it is necessary to study an analysis method using data that considers store closures.
2. The visualization method of showing the circular dispersion distribution in addition to the expanded directional map and the expanded directional trend distribution sometimes results in a large amount of information, making it difficult to grasp each phenomenon in some cases. Several measures can be considered in the future. A method to automatically detect and highlight the singular points of the vector field from each of the extended directional maps and extended directional trend maps is considered. In addition, since the data display function of a general GIS was used in this study, there are limitations in how the results can be visualized.
3. Although we have only proposed a method to capture the trend of change in commercial clusters based on past changes, we would like to study a future forecasting method to estimate the direction in which commercial clusters are expected to expand in the future, using the results of the analysis based on the method proposed here as test data.

We want to discuss the above issues and others in the future.

13.4.2 Summary and Future Prospects

Urban commercial areas are not only areas with many commercial stores but also places where many people live and are subject to many changes in social and economic conditions, either directly or indirectly. Many of these changes can be seen in the image of the area, the process of formation, and the direction of expansion, which is the subject of this study. The detailed and large amount of spatial data that has become easily available in recent years can be used to capture such urban events, as shown by previous studies and the method proposed in this study.

In this study, we propose an analytical method for extracting correlations among events and the formation process of events and their changes from a large amount of detailed spatial data and a visualization method that enables intuitive interpretation of the data and demonstrates its effectiveness. The methods were empirically validated using actual data from various events in an urban commercial area. On the other hand, the methods are based on a simplified model of events and do not necessarily reproduce real-life events perfectly. Therefore, it should be noted that the method is still insufficient for practical use in urban planning and urban development.

In this study, events such as the exit of a commercial store were treated in a simplified manner to increase the generality of the method. For example, only the opening of a store was treated due to data limitations. In the future, when data that is difficult to obtain, such as at the point of store exit, become available, it will be necessary to consider a method that more closely matches real urban events, including such data.

Next, the analysis of the method proposed in this study uses point data to simplify the method. Many of the events we try to capture in this study are complex and irregular changes and their trends in commercial areas. They are at the basic stage of capturing the nature and aspects of the events themselves. Therefore, to simplify the methodology, we used a point data format to precisely define each attribute, location, and time of occurrence to some extent. However, in an actual urban space, the scale of buildings has not a small influence on each event, and analysis using data such as polygon data, which includes the general area and scale of buildings, as well as the names of tenants, is also conceivable.

In the future, it will be necessary to examine the scale and area of buildings in three dimensions to represent the reality of urban space better. First, we would like to study an analysis method that adds area and other morphological information as attributes to the point data used in this study. Then we would like to develop an analysis method using polygon data that considers shape and scale.

Third, in this study, we could go back to when the latest available data was obtained and capture the changes that occurred during that period and their trends. In urban planning and urban development, it is often discussed in advance what effects a certain plan will have after its implementation and the current situation. The results obtained using the methodology developed in this study capture the trends of each urban event. Therefore, it is thought that using them as test data to predict future changes and transitions will be useful. In the future, it is necessary to consider using the results and findings obtained in each case for methods to clarify the prediction of future changes. The analytical method for this analysis is an issue for the future. The urban commercial areas in this study will be affected by rapid changes in various social conditions, which will accelerate various changes in urban space, such as the exit and exit of commercial stores and the formation of their image. Rapid changes in urban space will burden the lives of residents and various urban activities, and it will continue to be necessary to accurately understand the resulting urban events. In recent years, the development of information technology and ubiquitous technology has made it possible to acquire large amounts of detailed data to ensure a

more comfortable life for people. The quality and quantity of spatial data capturing various events will become better and richer, and there will be no shortage of such data in the future. Various spatial analysis and visualization methods have been developed to accurately and efficiently extract various events from these data. As mentioned in Chap. 1, the main objective of this study is to develop an analytical method that can capture trends and structures of events from detailed, diverse, and abundant data resources and derive hypotheses from them, even for exploratory spatial data analysis. As a result, it can be evaluated that each analysis method and visualization method developed in this study can derive hypotheses in an exploratory manner from a discussion of the results of each empirical analysis. We hope this research will serve as a basis for developing analytical methods to capture more advanced spatial phenomena.

References

- Akiyoshi I, Yukio S (2010): “A Method of Analysis and Visualization of Expanding Direction of Retail Distribution”, *Journal of the Architectural Institute of Japan* 75(650) 889–895. (in Japanese)
- Amin H (2007) Urban visualization with virtual reality. *Urban Plan Urban Visual Simul* 270:39–42
- Batty M (2003) Agent-based pedestrian modelling. In: Longley P, Batty M (eds) *Advanced spatial analysis. The CASA book of GIS*. ESRI Press, Redland, CA, pp 81–106
- Brunsdon C, Corcoran J (2006) Using circular statistics to analyse time patterns in crime incidence. *Comput Environ Urban Syst* 30(3):300–319
- Corcoran J, Chhetri P, Stimson R (2007) Using circular statistics to explore the geography of the journey to work. *Reg Sci* 88(1):119–132
- DiBiase D, MacEachren AM, Krygien JB, Reeves C (1992) Animation and the role of map design in scientific visualization. *Cartogr Geogr Inform Syst* 19(4):201–214
- Dorling D (1992) Stretching space and splicing time: from cartographic animation to interactive visualization. *Cartogr Geogr Inform Syst* 19(4):215–227
- Dykes J (1998) Cartographic visualization: exploratory spatial data analysis with local indicators of spatial association using Tcl/Tk and cdv. *R Stat Soc Statistician* 47(Part 3):485–497
- Dykes, Jason (2005): “Facilitating interaction for geovisualization”, In: Dykes, J, MacEachren, AM., and Kraak, M-J, (eds.): *Exploring geovisualization*, Elsevier, Oxford, pp. 143–158
- Fisher NI (1993) *Statistical analysis of circular data*. Cambridge University Press, Cambridge
- Gahegan M (2005) Beyond tools: visual support for entire process of GIScience. In: Dykes J, MacEachren AM, Kraak M-J (eds) *Exploring geovisualization*. Elsevier Ltd, Oxford, UK, pp 83–99
- Haining R (2003) *Spatial data analysis theory and practice*. Cambridge University Press, Cambridge, UK
- Hillier B, Hanson J (1984) *The social logic of space*. Cambridge University Press, Cambridge, UK
- Inoue R, Shimizu E (2005) A new method for constructing circle area cartogram. *Theory Appl GIS* 13(1):43–50
- Inoue R, Shimizu E, Yoshida Y, Li Y (2009) Visualization of spatial distribution and temporal transition of land Price in Tokyo 23 wards based on Spatio-temporal kriging interpolation. *Theory Appl GIS* 17(1):13–24
- Kigawa T, Furuyama M (2004) The urban entropy coefficient: a measure describing urban conditions—a morphological analysis on evolutionary process of Paris. *J City Plan Inst Japan* 39(3):823–828

- Kigawa T, Furuyama M (2005) Study on a vector in Kyoto's modernization by means of space syntax—a philosophy seen in an urban planning project for installation and broadening streets in Kyoto. *J City Plan Inst Japan* 40(3):139–144
- Kigawa T, Furuyama M (2006) Using space syntax to examine an evolutionary process of a local town—a case study on the modernization of Otsu city in Shiga prefecture. *J City Plan Inst Japan* 41(3):229–234
- Monmonier M, Watanabe J (1995) *Chizu Ha Usotsukidearu*, Shobunsha, Tokyo. Monmonier, Mark (1991): *how to lie with maps*. University of Chicago Press, Chicago, IL. (Translation).
- Roberts, Jonathan, C (2005): “Exploratory Visualization with Multiple Linked Views”, In: Dykes, Jason, MacEachren, Alan, M., and Kraak, Menno-Jan,(eds.): *Exploring Geovisualization*, Elsevier Ltd., Oxford, United Kingdom, pp.159–180
- Rodger, Peter (2005): “Graph Drawing Techniques for Geographic Visualization”, In: Dykes, Jason, MacEachren, Alan, M., and Kraak, Menno-Jan,(eds.): *Exploring Geovisualization*, Elsevier Ltd., Oxford, United Kingdom, pp.143–158
- Sadahiro, Yukio (2007): “From Spatial Analysis to Spatio-Temporal Analysis: Issues and Future Prospects”, *Urban Planning <Feature>: Beauty and Reality in Urban Analysis*, 264, pp. 31–35. (in Japanese)
- Shimizu K (2008) Recent developments in directional statistics: distributional aspects. *Japan Soc Comput Stat* 19(2):127–150
- Takamatsu S (2007) On visualization methods of form and function: developing techniques in the UK. *Urban Plan Urban Visual Simul* 270:13–16
- Theus M (2005) Statistical data exploration and geographical information visualization. In: Dykes J, MacEachren AM, Kraak M-J (eds) *Exploring geovisualization*. Elsevier, Oxford, p 127–142
- Yan W (2003) *GIS no Genri to Ouyou*. JUSE Press, Ltd, Tokyo. (in Japanese).
- Yoshikawa K (2007a) Application of 3D computer graphics to urban development: assuming its use in municipalities. *City Plan Urban Visual Simul* 270:43–46
- Yoshikawa M (2007b) Digital city and VR. *City Plan Urban Visual Simul* 270:47–50