Integrating Points-of-Interest and Areas-Of-Interest for Commercial Space Pattern Analysis

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Abstract. Commercial space pattern (CSP) analysis is an important topic in geographic research. Most studies on CSPs are conducted on a grid or block scale and therefore are unable to meet the requirements of refined CSP analysis. As geographic places that people can experience in urban environments, areas of interest (AOIs) provide a new research perspective for CSP analysis. Hence, a refined study on the CSP is presented, taking the Yuexiu district of Guangzhou as an example that integrates AOI and point-of-interest data extracted from AutoNavi Maps using kernel density analysis. The results show the following: the Yuexiu district has a multicore business development structure with relatively highly clustered business-operation AOIs. The approach in this study can help better discover business features, analyze more refined CSPs, and provide a new perspective for CSP research, making it valuable for understanding urban commercial spaces and optimizing commercial layouts.

Keywords: Commercial Space Pattern Analysis, Area of Interest (AOI), Point of Interest (POI), Kernel Density Analysis

1. Introduction
Commercial space pattern (CSP) analysis is an important topic in geographic research [1], and its current characteristics serve as a key factor in urban planning [2]. The optimization of business layouts in urban commercial spaces is of great significance to the accelerating urban economic development, meeting the consumption demand of urban residents, and improving the urban spatial structure [3]. With the progression of urbanization, urban commerce in China has entered a rapid development stage. Recent studies on commercial spaces have accordingly shown a new trend with modern characteristics [4]. In traditional studies, a mature theoretical basis regarding the development and evolution, structural characteristics and spatial layout, and functions of urban commercial spaces has been established [5]. However, the data used in these studies were based on statistical documents and economic census data, which not only required large amounts of time and labor but also had the disadvantages of poor accuracy and comprehensiveness and low updating frequency. Thus, the traditional methods do not meet the demands for quantitative urban commercial analysis and urban economic development in the information age.
With the rapid developments in big data analytics and massive data collection in recent years, new data sources, including mobile phone signaling data, street images, and point-of-interest (POI) data, emerge continuously [6-7]. These types of data usually have the features of massive data volume, large coverage, high precision, and frequent updating. Therefore, these data sources can more accurately reflect various social activities and the spatial distribution of geographic objects, thereby providing a new research perspective for urban commercial studies [8]. In particular, the geographic entities that are closely related to urban commercial activities as shopping malls, restaurants and financial institutions can be extracted as POI data, which is an important data type in urban commercial space studies. POI data provide a new perspective for solving urban commercial problems. However, the existing studies on commercial space layouts were mostly based on POI data only and were subject to the influence of large spatial heterogeneity in the data distribution. Moreover, the assessment of the commercial space pattern in these studies was conducted on a grid or block level and failed to describe the geographic space of the commercial places in a finer manner. Therefore, based on POI data only, it is hard to perform a refined quantitative analysis of a commercial place regarding its degree of clustering of businesses, business diversity, and business model.

The rapid development of Internet maps offers a convenient, efficient method for determining geographic places. When a search is conducted for a shopping mall, a mask layer will appear on AutoNavi Maps. This layer is the AutoNavi Maps area of interest (AOI). As a leading map service provider in China, AutoNavi Maps provides data for millions of AOIs within China and thereby provides reliable data support for applications such as map navigation and location selection for merchants. Web crawlers can be used to rapidly determine the boundaries of geographic places, such as residential compounds, shopping malls, scenic areas, and schools. In addition, each AOI exists around a core area. AutoNavi Maps AOI data provides us with convenient, accurate, and rapid data sources for refined urban studies. Thus, by integrating POI data and AutoNavi Maps AOI data, we performed refined CSP analysis.

2. Study Area, Data Sources and Methods

2.1 Study Area and Data Sources
In this study, the commercial spaces in the Yuexiu district of Guangzhou, Guangdong Province, China, are analyzed on an AOI scale. Situated at the center of Guangzhou, the Yuexiu district encompasses a total area of 33.80 km² and is home to a number of famous commercial and trade areas, including Beijing Road, Hero Square, China Plaza, and TeeMall Plaza. Commercially, this district is highly developed, but the CSP varies notably in this district.

Using the web crawler technique, a total of 1,828 AOI data points for January 2020, including the number, name, type, and address fields, were collected from AutoNavi Maps. A total of 65,841 business POIs in the Yuexiu district, belonging to 12 types (including catering, life, shopping, accommodation, automotive, and financial and insurance services), were obtained based on the POI and keyword search interfaces of the AutoNavi Maps application programming interface. The POI data fields include the identification, name, longitude and latitude, primary type, secondary type, tertiary type, and address.

An overlay analysis found that 227 AOI data points (mostly for schools and government agencies) contained no business POI data. These data were treated as junk data and removed. Ultimately, 1,601 AOI data points were preserved for analysis. These data involve nine types of AOIs, namely, commercial residences, accommodation services, scientific, educational, and cultural services, transport facility services, sports and recreational services, scenic and historical areas, shopping services, automotive services, and healthcare services. There are 1,091 AOIs for commercial residences, accounting for the majority (68.15%) of the AOIs. Figure 1 shows the spatial distribution of the reclassified AOIs.
In addition, 11,379 data points were not overlaid on the AOI data. These data points were treated as noise points and eliminated. The preserved 51,462 POIs involved 63 secondary types. POIs relating to five secondary types, namely, specialty boutiques; shopping service–related places; clothing, shoe, hat, and leather goods stores; beauty and hair salons; and food-related places, accounted for 52% of all the preserved POIs. Thus, this study examines a more refined CSP based on the secondary-type field. Figure 2 shows the spatial distribution of the POIs used in this study.

2.2 Research Methods
KDE is one of the nonparametric test methods used in probability theory to estimate unknown density functions. Proposed by Rosenblatt (1955) and Parzen (1962), KDE estimates the density of a point or line pattern based on a moving cell. Conceptually, there is a smooth surface that covers the point from above. The maximum of the data appears at the point. As the distance from the point increases, the surface value gradually decreases. The surface value is 0 one search radius away from the point. When data are output in the raster form, the density of each output raster pixel is the sum of the values of the kernel surfaces overlaid at its center. Generally, the kernel density of business POIs in a study area with P as its center is as follows:

$$f(s) = \frac{1}{nh} \sum_{i=1}^{n} k \left( \frac{x_i - x}{h} \right)$$

Where $f(s)$ is the function for calculating the kernel density at the spatial location $s$, $n$ is the number of commercial activity factors within the distance-scale range, $h$ is the distance threshold (i.e., the scale of the KDE method), $(x, x_i)$ is the Euclidean distance between two points, and $k$ is the weight parameter of the commercial activity factors. In KDE, the distance decay threshold $h$ is a free parameter that defines the amount of smoothing. An overly large or small $h$ will directly affect the result of $f(s)$. 

**Figure 1.** Spatial distribution of AOIs
3. Results

In this study, the spatial clustering of businesses is examined using the KDE method. The higher the kernel density is, the higher the degree of spatial clustering is, and vice versa. In kernel density analysis, \( h \) directly affects the result. Based on previous studies and the results of multiple experiments, \( h \) and the pixel size were set to 200 m and 20×20 in this study, respectively. As shown in Figure 2, overall, commercial facilities are relatively widely distributed in the Yuexiu district. Commercially, this district is relatively highly developed. However, there is significant spatial heterogeneity. Three notable business clusters have been formed in the northwest, central, and southwest of the Yuexiu district. Business development in the Yuexiu district exhibits a multicore structure. Businesses are the most highly clustered in the northwestern Yuexiu district, where business development is relatively mature. There are also some relatively highly developed secondary business clusters surrounding the three notable clusters due to the distance decay effect.

![Figure 2. Kernel density analysis results](image)

To more finely analyze the business development in the Yuexiu district, the kernel density analysis results were spatially overlaid with the AOI data, and the kernel densities within each AOI were summed. In addition, normalization was performed based on the area of each AOI to determine the kernel density of each AOI per unit area. As demonstrated in Figure 3, there are businesses distributed in each AOI, but the degree of clustering of businesses varies relatively significantly between AOIs. There is a notable spatial heterogeneity in terms of business development. The degree of clustering of businesses is the highest in the Beijing Road Pedestrian Zone. Commercial facilities are highly clustered in several geographic places in this area, including the Dafo Temple, TeeMall Plaza, and the Guangzhou Grandbuy Department Store. In addition, businesses are relatively highly clustered in and surrounding a number of geographic places with business operations, including China Plaza, the Kwangchow Friendship Store, the Wangfujing Mansion, Wanling Plaza (Jiefang South Road location), and Central Plaza. In comparison, the degree of clustering of commercial facilities is relatively low in commercial/residential and convenience-service AOIs.
Summary
CSP analysis is an important topic in geographic research. Conventional CSP research is based mostly on the grid or block scale. There is a lack of refined research on CSPs. Based on AutoNavi Maps AOI data, this study examines a refined CSP on a geographic-space scale. Below, we summarize the findings on the CSP in the Yuexiu district. Business clusters are evaluated by KDE. It is found that three notable business clusters have arisen, in the northwestern, central, and southwestern parts of the Yuexiu district, respectively. The business development in the Yuexiu district exhibits a multicore structure. Businesses are relatively highly clustered in business-operation AOIs. The degree of clustering of businesses is the highest in the Beijing Road Pedestrian Zone. In comparison, the degree of clustering of businesses is relatively low in commercial/residential and convenience-service AOIs.

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