Extracting hierarchical landmarks from urban POI data

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Abstract: For acquiring the hierarchical spatial knowledge to be applied in cognitive route directions, a method of extracting hierarchical landmarks from urban POI data according to their significances is proposed. After analyzing the factors influencing the significances of POI objects from public cognition, spatial distribution and individual characteristics, a significance measure model composed of three vectors which are public cognition degree, urban centrality degree and characteristic attribute value is constructed. Then, the processes of computing the vector values of POI objects are discussed by the methods of questionnaire survey, multi-density spatial clustering and data normalization respectively. An experiment is carried out to compute the significances of the POIs selected from the area of Wuchang region of Wuhan city, and the POIs with different significances are treated as landmarks in different levels at last. In this experiment, several levels of landmarks are extracted, and being used as seeds to compute weighted Voronoi diagrams in every level, to reflect the influence area of every landmark and associate the landmarks in the same level and between the sequential levels.

Key words: navigation, spatial knowledge, landmark, POI, hierarchy

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1 INTRODUCTION

Route directions of navigation system consist of two basic processes, describing the location of a decision point on the route, and then instructing the action should be carried out at the decision point (Daniel & Denis, 1998). When the user is completely strange to the environment, all the decision point / action pairs should be declared in sequence with or without spatial chunking (Klippel, *et al.*, 2009). However, for people with a priori knowledge of the environment, only some salient places being known on the route need to be described to approach the destination (Tomko & Winter, 2009). Combing these two modes to make route directions more intelligent and cognitive is the development orientation of next-generation navigation system.

A shared hierarchical structure of spatial knowledge should be constructed and reasoned to realize that navigation mechanism. Lynch (1960) categorizes physical features of the urban environments into five types of elements, which are nodes, paths, edges, districts and landmarks, to reflect the bodily experience acquired during exploration and traveling through the environment. Today it is a common view that everything that stands out of the background may serve as a landmark (Raubal & Winter, 2002). However, in this paper we limit ourselves to Lynch's view, and consider landmarks as point-like elements in the city. According to Siegel and White's research on spatial cognition, landmark knowledge characterizes the discrete knowledge of salient spatial features, and it is integrated into more complex structures to form the spatial knowledge of environmental conformation and distribution (Siegel & White, 1975). A landmark forms an anchor of its reference region (Kettani & Moulin, 1999), in which the landmark is unique and dominant, and the prominence of a landmark determines the size of its reference region. Winter, *et al.* (2008) hierarchizes landmarks based on their individual salience and use Voronoi polygons to represent their reference regions, with the purpose of applying them in the granular description of places and routes.

Extracting landmarks from the environment is a grand issue of spatial cognition. Based on Sorrows and Hirtle's (1999) identification of aspects that constitute a landmark, which are visual aspect, structural aspect and cognitive aspect, some scholars developed some measure models defined on those three indicators for determining a landmark's saliency (Raubal & Winter, 2002; Nothegger, *et al.*, 2004; Klippel & Winter, 2005). Compared to those models,

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Caduff and Timpf (2008) introduces a more complicated salience-assessing framework, containing three types of salience, which are perceptual salience, cognitive salience, and contextual salience, to reflect the relations among spatial features, surrounding environments and the observer's point of view with Bayesian networks. In a different approach, methods from data mining are employed to identify those objects in a surrounding that are salient by Elias (2003). In this approach, saliency is defined as either objects with a short description tree (ID3), or objects that are singled out early on in clustering (Cobweb). However, as all the above approaches trying to automatically identify suitable landmarks from a set of candidates require a rich and reliable data set offering information in different dimensions, they are hard to be implemented and widely used since such data is hard to get and maintain. Furthermore, the identification process may involve complex, lengthy calculations, and correctly setting the parameters requires much and difficult empirical testing. Some other scholars explored augmenting automatic route directions with landmark information extracted from the digital documents collected from the World Wide Web (Tomko, 2004; Tezuka & Tanaka, 2005). However, it is impossible to process all searched data, and the search queries' identification of the correct location can be problematic.

For making the extraction of landmarks easier to achieve, this paper proposes a method of extracting landmarks from points of interest (POIs) of the urban environments. All the physical features abstracted as points, especially the facilities closely related to people's lives, such as shopping malls, railway stations and schools, could be called POIs, which constitute important contents of navigation electronic maps (ISO, 2004). Every POI object with specific influence area can be treated as a landmark, and the significances of POIs is the basis of landmark hierarchization. The remainder of this paper is organized as follows. Section 2 analyses the factors influencing the significances of POI objects and constructs a measure model to compute them. Section 3 discusses the methods for computing all the significance vectors in the model. In section 4 an experiment of significance computation and landmark hierarchization is carried out. Finally, section 5 concludes our proposition and outlines future works.

2 FACTORS INFLUENCING THE SIGNIFICANCE OF A POI

This section discusses the factors influencing the significances of POI objects from public cognition, spatial distribution and individual characteristic, and proposes a significance measure model based on three corresponding vectors, called public cognition degree, urban centrality degree and characteristic attribute value.

2.1 Public cognition

When interacting with the environments, we usually cognitively group spatial knowledge into some categories, to represent our beliefs about the world (Mennis, *et al.*, 2000). Although the cognitive abilities and cognitive outcomes vary, some shared knowledge can be found through plenty of surveys, to facilitate our comprehension and communication of the environment (Lynch, 1960). Therefore, the pubic cognition degree of every POI category which reflects the public awareness of its significance can be discovered through extensive surveys.

Although every POI object has specific influence area and concerned groups, there are some categories of POIs intensively distributed and rarely cognized, such as convenience stores and small restaurants, which are inappropriately regarded as significant landmarks in the city. Hence, only such categories of POIs as railway stations and shopping malls, being well known, functionally important and huge in size, are discussed and cognitively surveyed in this paper. We divide these POIs into 11 categories whose denominations and domains are defined in Table 1.

Table 1 POI Categories discussed in this paper

Denominations	Domains
Shopping centers	department stores, theme emporiums, super markets
Luxury hotels	three star hotels and above, large restaurants
Transportation hubs	railroad or bus stations, airports, ports
Urban parks	comprehensive parks, theme parks, squares
Places of interest	famous landscape, monuments, memorials
Leisure venues	stadiums, theaters, cinemas
Important organs	party and government organizations of districts and higher levels
Educational institutions	colleges, universities, cultural centers, museums, galleries
Major hospitals	general and specialized hospitals in first or second class
Tall buildings	large office building and commercial buildings
Residence communities	all kinds of residential areas

2.2 Spatial distribution

As the centralized areas of commerce, services, community facilities and so forth, urban centers have high accessibility, and are attractive to various activities of people (Lynch, 1984). Therefore, the POIs in urban centers are more easily cognized by the public and are more significant than the others. There are multiple levels of centers in a city, where the dominant center includes all the "highest", or most intense, or most specialized activities, while the sub-centers which serve only portions of the community contain less important, less intense, or less specialized activities (Lynch, 1984). Hence, the urban centrality degree of every POI object which reflects the level of urban center it locates can be discovered through multi-density spatial clustering.

The variation of spatial distribution densities of POI data reflects different levels of urban centers: the highest density clustered area usually represents the dominant center, and the lower density clustered areas represent the sub-centers. The clustered areas of POIs discovered through multi-density spatial clustering are usually nested with each other, as shown in Fig.1. In this example, according to the difference of density, the urban centrality degrees of POIs in circular area A are higher than the POIs in annular area B.

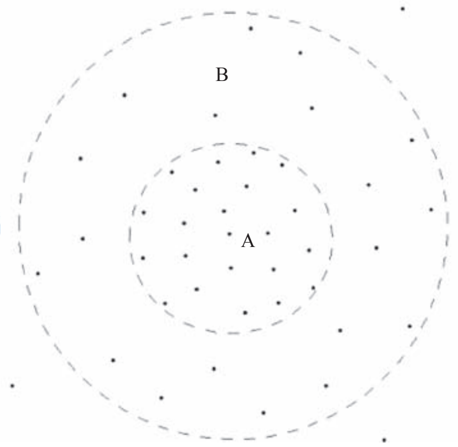

Fig. 1 Hierarchical POI clustered areas

2.3 Individual characteristic

The significances of landmarks are mainly measured by observing their visual, structural and semantic qualities which make them prominent from the surroundings, due to differences in size, shape, position, role or cultural importance (Sorrows & Hirtle, 1999; Nothegger, *et al*., 2004; Klippel & Winter, 2005). Judging to the POIs, their semantic and structural significances are respectively determined by their categories and spatial distribution, and can be respectively reflected from their public cognition degrees and urban centrality degrees. While the significances in the visual aspect of POIs can be determined by their characteristic attributes such as sizes and grades. Therefore, the significant distinctions of POIs in individual characteristic can be reflected through collecting and comparing their characteristic attribute values.

The variations representing the characteristic attributes of POIs may resort to interval scale, such as the business areas of shopping centers, or ordinal scale, such as the star rating of hotels. For the purpose of eliminating the dimensional difference of the attribute data and achieving the hybrid application of quantitative and qualitative numeric values, the characteristic attribute values of all the POIs should be normalized, which means all the original attribute values with various measurement methods are transformed into the same interval. As a result, the significant distinctions of POIs of different categories can be represented in a uniform and reasonable manner.

2.4 The significance measure model of POI

From the above, the public cognition degree (Cog. in abbreviation), urban centrality degree (Cen. in abbreviation) and characteristic attribute value (Char. in abbreviation) of a POI object can comprehensively reflect its significance (Sig. in abbreviation). For that reason, a significance measure model of POIs composed of these indicators is proposed in this paper as follows.

$$\text{Sig.} = c_1 \times \text{Cog.} + c_2 \times \text{Cen.} + c_3 \times \text{Char.}$$

In this model, the weight coefficients of the three vectors, c_1, c_2 and c_3, must sum to 1, and the values of the three vectors should be normalized into the interval of [0, 1] to eliminate the difference of dimensions. The values of these weight coefficients are usually set according to specific cognitive experiments to make the order of the significances of all the POIs basically conforms to the spatial cognition results of most people. Furthermore, the determined coefficient values may be appropriately modified to meet the diversity of different user groups in preferences, cognitive habits and living environments, *etc*.

3 COMPUTATION OF THE SIGNIFICANCES OF POI

On the basis of the significance measure model of POIs proposed in last section, three methods, public cognition survey, multi-density spatial clustering and characteristic attribute normalization, are introduced to respectively calculate those three significance indicators of POIs defined in the model.

3.1 Public cognition survey

Sampling survey is an important method to discover shared knowledge (Lynch, 1960). Based upon the 11 POI categories defined in section 2.1, questionnaire survey is applied to ask the respondents, which are mostly young and middle-aged people living in urban environments, to make a judgment of whether the POIs of every category are “not significant”, “not very significant”, “generally significant”, “rather significant” or “quite significant” as landmarks of the surroundings. According to the 5-point Likert scale, these five judgments are respectively assigned to values between 1 and 5.

This survey totally received 233 questionnaires, and the respondents are balanced in gender, widespread in occupation and mostly live in cities for more than 5 years. After calculating the means and standard deviations of the statistical data with the SPSS software, the public cognition degrees of all the POI categories can be acquired through normalizing their means, as shown in Table 2, with the descending order of the means.

Table 2 Public cognition degrees of POIs of every categories

POI Categories	Means	Standard deviations	Public cognition degrees
Transportation hubs	4.4449	0.69148	1.0000
Places of interest	4.0529	0.87078	0.8245
Shopping centers	4.0308	0.84870	0.8146
Educational institutions	3.7093	0.97038	0.6706
Urban parks	3.6740	0.88217	0.6548
Luxury hotels	3.4537	0.93189	0.5562
Major hospitals	3.3436	0.88046	0.5069
Leisure venues	3.3304	0.89299	0.5010
Important organs	3.0044	1.04964	0.3550
Tall buildings	2.8943	0.96730	0.3057
Residence communities	2.2115	0.87707	0.0000

According to the statistical results shown in above table, residence communities are unsuitable for significant landmarks as their public cognition degrees are quite low. Hence, only the left 10 POI categories are necessary to the POI database for extracting landmarks. Besides, there may be some redundant data in POI database; for instance, both the shopping centers and their located tall buildings may be included, and some organs may be located in the same place. Therefore, before carrying out the next operation, the POI database should be preprocessed to get rid of the redundant data, and only the POIs with higher public cognition degrees or characteristic attribute values need to be preserved.

3.2 Multi-density spatial clustering

In this paper, the density-based OPTICS algorithm, which can create an augmented ordering of the database representing its density-based hierarchical clustering structure (Ankerst, *et al.*, 1999), is employed to cluster the POI data into several areas with different densities for estimating their urban centrality degrees. In order to conveniently observe the clustering results for choosing the appropriate parameters of the maximum clustering radius ε and the minimum number of clustered objects (MinPts), we improve the traditional OPTICS algorithm on its data process manner, by directly recording core-distances, reachability-distances and other information of the POIs in the database, and explicitly designating the subordinate relations between the core objects and the non-core objects. This algorithm can be implemented through five steps as follows.

Step 1 Initializing the database

Add some fields in the POI table of the database to record the flags of whether been processed, the flags of whether being core objects, core distances, reachability distances, belonged core objects and so on. Then, mark every POI object unprocessed and assign the other fields default values.

Step 2 Constructing clustering sets

Beginning with every POI object which is unprocessed and conforms to the core object condition that the ε-neighborhood of the object has to contain at least MinPts objects, combine all the unprocessed objects which are density-reachable from the beginning objects into some clustering sets. Then, mark all the objects in the sets processed, and mark all the objects conforming to the core object condition in the sets core objects. Meanwhile, the core distances of the core objects are calculated and recorded.

Step 3 Filtering core objects

Compare the actual distance of any two core objects in every clustering set and the sum of their core distances. If the former is equal or less than the latter, re-mark the object with larger core distance non-core object and modify its core distance into default value. Otherwise, preserve their original attributes.

Step 4 Determining high-density clusters

The objects in the neighborhood of a core object with the radius of its core distance are defined as a high-density cluster. The reachability distances of the objects in every high-density cluster are all recorded as the core distance of the core object in the cluster, and the belonged core objects of the non-core objects in every high-density cluster are all recorded as the core object in the cluster.

Step 5 Classifying the left objects

For every non-core object in every clustering set whose belonged core objects is undetermined, find the closest core object to it and calculate their actual distance. If the distance is less than ε, its belonged core object is recorded as the closest core object, and its reachability distance is recorded as the actual distance. Otherwise, the object is treated as clustering noise.

After being processed in accordance with above five steps, the POI data can be clustered with multiple density grades. And then, all the POI objects except for the noises can be classified into N levels of clustered areas, through setting N clustering distances ε'_n in ascending order where $\varepsilon' < \varepsilon$ and $n \leqslant N$, and searching for the POI objects whose reachability distances are equal or less than ε'_n and greater than ε'_{n-1} when $n > 1$.

Besides the noise objects whose urban centrality degrees are assumed to be 0, all the other POI objects are assigned values from N to 1 according to the density grades of the clustered areas at which they locate. Afterwards, the urban centrality degree of every POI object can be obtained through linearly transforming the density grade values into the interval of [0, 1].

3.3 Characteristic attribute normalization

The characteristic attributes of different categories of POI objects are usually measured with different indicators, such as business areas, occupancy areas, construction areas and floor numbers are respectively used to measure the characteristic attributes of shopping centers, urban parks, leisure venues and tall buildings. Although min-max normalization can be used to process these indicators, as this method is susceptible to the extreme values, the more reasonable way is firstly dividing the POI objects of every category into several grades with appropriate standards and then normalizing the grade values into the same interval. Furthermore, the POI objects of the same main category but different sub-categories may also be incomparable, such that the significances of comprehensive parks and squares don't simply depend on their occupancy areas. Therefore, the POI objects of different sub-categories need also be classified in different ways sometimes.

The POI objects of the other categories defined in this paper can be classified with qualitative indicators. The hotels, hospitals and places of interest can be clearly classified with uniform national or industry standards, such as five-star hotels and upper first-class hospitals. Nevertheless, the size of educational institutions and important organs can be classified with some common-sense knowledge. For example, the universities may be classified into universities directly under MOE, provincial universities, municipal universities and private universities; the organs may be classified into state-level organs, province-level organs, bureau-level organs and county-level organs.

After classifying the POI objects of different categories into several grades with appropriate standards, and linearly transforming the grade values into the interval of [0, 1], the characteristic attribute value of every POI object can be uniformly measured in the same criterion.

4 EXPERIMENT

According to the POI selection domains defined in section 2.1, 556 POI objects were selected from the Wuchang region of Wuhan city in Hubei province to make the experiment of hierarchical landmark extraction, including 119 luxury hotels, 115 shopping centers, 113 educational institutions, 74 important organs, 39 tall buildings, 33 major hospitals, 21 places of interest, 21 leisure venues, 14 urban parks and 7 transportation hubs.

Firstly, these POI objects were clustered using the multi-density spatial clustering algorithm proposed in section 3.2, while ε and MinPts were respectively set as 4 km and 25. The clustering result was visualized by virtue of the ArcScene software, shown as Fig. 2, where the reachability distances of the POI objects represented with columns are in inverse proportion to the heights of the columns, and the POI objects represented with dots are noises. All of the POIs in Fig. 2 were naturally broken into 5 groups, respectively corresponding to the urban centers in 5 grades. As the urban centers with the highest grades are Zhongnan area, Jiedaokou area, Simenkou area, Optics Valley area and Xudong area, the grading is basically in accordance with the public cognitive results of the urban center distribution in Wuchang. As a result, the urban centrality degree of every POI object was obtained after being assigned a grade value between 5 and 1 and then being linearly transformed into the interval of [0, 1].

Next, the characteristic attribute of every POI object was normalized, and the public cognition degree of every POI category determined in section 3.1 was assigned to every POI object. As the POI data provided by the navigation data producers are commonly short of characteristic attributes, thus, internet search and field investigation were applied to gather the characteristic attributes of POI objects. Meanwhile, the POI objects of every category were divided into several grades according to existing standards or common-sense knowledge. After assigning the POI objects with higher grades larger grade values and then normalizing them, the characteristic attribute value of every POI objects was at last obtained.

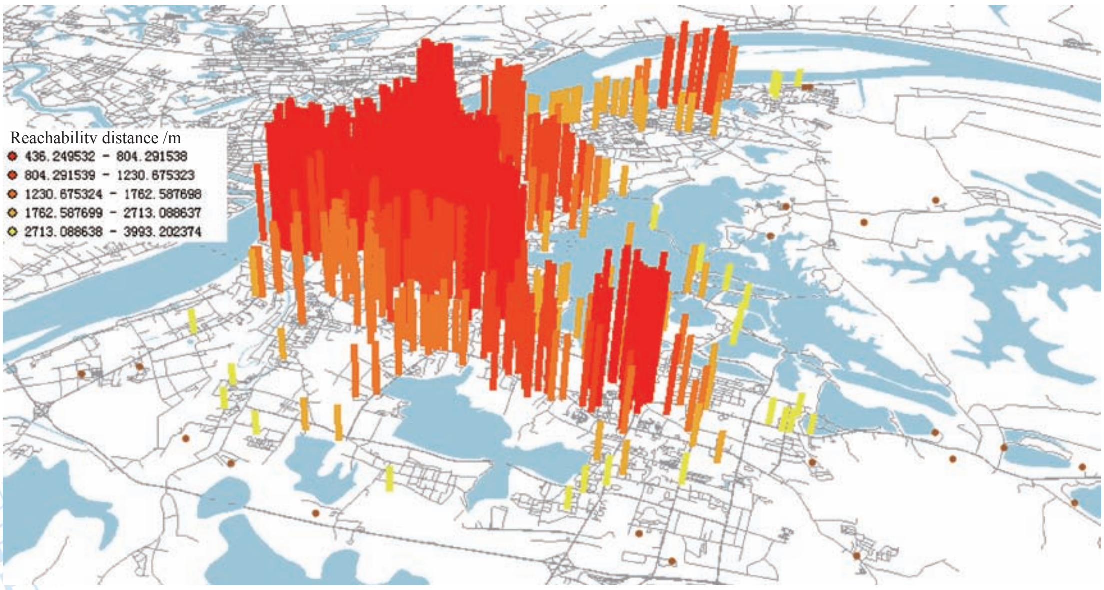

Fig. 2 Multi-density spatial clustering result of the POI data

After the public cognition degree, urban centrality degree and characteristic attribute value of every POI object being determined, its overall significance can be calculated by means of the significance measure model proposed in section 2.4, with appropriate weight coefficients assigned to the vectors of the model. If the weight coefficients are appropriately set, the calculation results of the significances of the POI objects can be widely accepted by the public, and can reflect the individual differences of the users in preferences, cognitive habits, living environments and so on as occasion requires. In this experiment, expert evaluation method was adopted to analyze and compare the rationality of the calculation results acquired through utilizing several groups of representative weight coefficients in the model. In the end, the weight coefficients of the vectors standing for the public cognition degree, urban centrality degree and characteristic attribute value were respectively set as 0.4, 0.2 and 0.4. The intermediate and ultimate significance calculation results of several very significant POI objects are listed in Table 3, which is not completely consistent with the recording mode of the POI database for the purpose of improving the intelligibility. As shown in Table 3, the characteristic attributes of various categories of POI objects were all divided into 5 grades, where the hotels and places of interest were graded in accordance with established industry standards, the shopping centers and squares were respectively graded according to their business areas and occupancy areas, and the transportation hubs and educational institutions were graded in accordance with common-sense knowledge.

The POI objects with different significances can be regarded as landmarks to reflect spatial knowledge with different granularities. The most significant landmarks are usually very influential in the whole city, while the lower significant landmarks are usually only influential in some local areas. For example, in route directions, some most significant landmarks are firstly selected to decrease the cognitive efforts of the requesters, and then some lower significant landmarks are selected to gain greater cognitive effects on the requesters when necessary. Therefore, all the landmarks can be organized into hierarchical structures according to their significant differences, for the responders to select appropriate landmarks according to specific requirements. It is worth noting that the hierarchical structures of landmarks are different from the hierarchical structures of districts. Every district on a higher level is partitioned into several non-overlapping smaller districts on the lower level, whereas every landmark on a higher level is still present on the lower level and the roles of landmarks on different levels are usually different. For instance, Yellow Crane Tower can be used as a global landmark in Wuhan, and also be a local landmark of its neighborhood.

According to the calculation results of POI significances, 5 levels of landmarks, whose significances are respectively larger than 0.85, 0.82, 0.76, 0.65 and 0, were extracted from the POI data in this experiment. The numbers of landmarks of the 5 levels were

Table 3 The significance calculation results of several POI objects

No.	Name	Characteristic atribute	Characteristic grade	Reachability distance/m	Clustering grade	Public cognition degree	Urban centrality degree	Characteristic attribute value	Significance
1	Yellow Crane Tower	5A scenic spot	5	634.9	5	0.8245	1.0	1.0	0.9298
2	Wuhan Chicony Plaza	90, 000 m^2	5	586.9	5	0.8146	1.0	1.0	0.92584
3	Optics Valley International Plaza	60, 000 m^2	5	705.1	5	0.8146	1.0	1.0	0.92584
4	Wuchang Railway Station	—	5	1281.5	3	1.0000	0.6	1.0	0.9200
5	Wuhan Shopping Mall	173, 000 m^2	5	838.8	4	0.8146	0.8	1.0	0.88584
6	Hongshan Square	108, 000 m^2	5	436.2	5	0.6548	1.0	1.0	0.86192
7	Comptown Information Plaza	30, 000 m^2	4	586.9	5	0.8146	1.0	0.8	0.84584
8	Intime Department Store	30, 000 m^2	4	488.0	5	0.8146	1.0	0.8	0.84584
9	Zhongnan Shopping Center	30, 000 m^2	4	488.0	5	0.8146	1.0	0.8	0.84584
10	Luxiang Shopping Center	50, 000 m^2	4	705.1	5	0.8146	1.0	0.8	0.84584
11	Wuhan Computer Plaza	32, 000 m^2	4	586.9	5	0.8146	1.0	0.8	0.84584
12	Optics Valley Grand Ocean Department Store	33, 000 m^2	4	705.1	5	0.8146	1.0	0.8	0.84584
13	Fujiapo Bus Station	—	3	488.0	5	1.0000	1.0	0.6	0.8400
14	Hubei Provincial Museum	—	5	1074.1	4	0.6706	0.8	1.0	0.82824
15	Wuhan Mayflower Hotel	5 star hotel	5	488.0	5	0.5562	1.0	1.0	0.82248

respectively 6, 19, 69, 223 and 556, and the landmarks of higher levels were always the subsets of the landmarks of lower levels. In the hierarchization result, the first-level landmarks included Yellow Crane Tower, Wuhan Chicony Plaza, Optics Valley International Plaza, Wuchang Railway Station, Wuhan Shopping Mall and Hongshan Square, the second-level landmark included Luxiang Shopping Center, Ramada Plaza Optics Valley Hotel, Optics Valley Grand Ocean Department Store, Guangbutun Information Plaza, Wuhan Computer Plaza, Hubei Provincial Museum, Zhongnan Shopping Center, Intime Department Store, Hongguang Hotel, East Lake Hotel, New Beacon International Hotel, Mayflower Hotel and Fujiapo Bus Station, besides all of the first-level landmarks. Due to the limitation of paper length, the landmarks of the other levels are not enumerated here.

The more significant a landmark is, the larger its spatial influence area becomes. Therefore, the reference region of every landmark can be reflected by its Voronoi polygon after a weighted Voronoi partition is created, where the landmarks in a level are used as the seeds and their significance values are used as the weights. Besides, the landmarks used as seeds are the most significant landmarks in their reference regions. The Voronoi partition results of partitioning the space with the highest four levels of landmarks utilizing the algorithm of weighted Voronoi diagram generation proposed by Dong (2008) are shown in Fig. 3. Since the major processing steps are raster-based, it is possible that several landmarks share the same Voronoi polygon if those landmarks are very close to each other and raster cell size is not small enough, such as Optics Valley International Plaza, Luxiang Shopping Center, Ramada Plaza Optics Valley Hotel, and Optics Valley Grand Ocean Department Store in this experiment. As those landmarks are aggregated in very small spatial range, the rationality of the spatial partition is not affected. The cell size is the shortest of the width or height of the extent of input feature layer, in the output spatial reference, divided by the cell size factor (default to 250). Hence, if the coverage areas of all the levels of landmarks are different, the raster divide results of these levels are also different when generating Voronoi diagrams. When several landmarks are located in the same raster cell, the most significant landmark, or one of the most significant landmarks, should be selected as the representative landmark of the raster cell.

The hierarchical Voronoi diagrams built upon the hierarchical landmarks can be used to infer the cognitive effort and cognitive effect of retrieving the spatial knowledge of every landmark during route communication. Every landmark can be characterized by the current level I at which it is used in discourse, and by the maximal level M at which it appears in the leveled hierarchy, with $I \leqslant M$. The smaller M value is, the larger the spatial influence area of the landmark becomes and then the lower the cognitive effort becomes. The larger I value is, the clearer the spatial context of the landmark becomes and then the greater the cognitive effect becomes. In route directions, the dominant landmark of the Voronoi polygon in the lowest level, at which the destination locates, provides the greatest cognitive effect. If the M value of the landmark equals 1, it also provides the lowest cognitive effort, and the hearer may be aware of the approximate location of the destination after the landmark is described. Otherwise, other landmarks with lower M value should be found out and introduced, by virtue of the contextual inclusion relations between landmarks in different levels, to decrease the cognitive effort of the hearer. As the size of the Voronoi polygon size of every landmark determines the contextual certainty of the landmark in current level, the contextual inclusion relations between the hierarchical landmarks can be constructed from the covering relations between the Voronoi polygons in the hierarchical Voronoi diagrams. The hierarchical landmarks can be represented as tree-like structures, where some landmark may belong to several superordinate elements; meanwhile, some landmarks are their own superordinate elements.

Besides, the Delaunay triangulation which is the dual structure of the Voronoi diagram in R^2 can be used to construct the adjacency relations between landmarks in the same level. Representation and

(a) (b)

(c) (d)

Fig. 3 Hierarchical landmarks extracted from POI data
(a) Firest-level landmarks (Sig. > 0.85); (b) Second-level landmarks (Sig. > 0.82);
(c) Third-level landmarks (Sig. > 0.76); (d) Fourth-level landmarks (Sig. > 0.65)

reasoning of regional spatial knowledge conforming to the law of spatial cognition of people can be realized if an appropriate data structure is constructed to describe the inclusion relations of landmarks between the sequential levels and the adjacency relations of landmarks in the same level. For example, in the application of navigation, simple, flexible and efficient route directions could come true after a sequence of landmarks, which are known to the users, close to the destination, and most relevant to the real-time locations, are interactively found out from the data structure, appropriately reasoned out with inference rules, and accurately described to the users.

5 CONCLUSION

The POI significance influencing factors presented in this paper, which are the public cognition, spatial distribution and individual characteristic, can comprehensively measure the significance of every POI object in semantic, structural and visual aspects. Although the significances of POI objects may also be influenced by other factors to some extent, such as specific contexts of the environments and cognitive abilities of the users, those factors were not considered in this paper because they are too variable or subjective to construct public spatial knowledge structure. With regard to the POI significance measure model, the calculation results based on it could basically conform to the public cognition of POI significances if the vectors constituting the model are assigned appropriate weight coefficients. Expert evaluation method was effective to determine these coefficients. This method is composed of three steps: firstly, several groups of representative coefficients are selected to respectively compute the significance of every POI object; then, some experts are invited to give marks to those calculation results; at last, the group of coefficients with the highest scores is chosen as the default coefficients of the model. Furthermore, considering the individual differences of the users in preferences, cognitive habits and living environments, the default coefficients could also be modified to adapt to different applications. For instance, the coefficient of public cognition degree of a category of POI objects can be magnified, to promote the significances of the POI objects of that category.

Compared to traditional landmark significance measure methods which need collect plenitudinous property data of individual spatial features, such as their geometrical and semantic information, the method proposed in this paper researches on the categories, spatial distribution and characteristic attributes of POI data. As the data are easy to acquire, process and update, this method is efficient, pragmatic and easy to implement. In order to generally survey the public cognition degrees of POI categories, the respondents were evenly sampled in genders, ages, occupations and years of living in the cities. However, in practice, the cognitive differences between different target groups, such as women, the elderly and teachers, could be distinguished to gain customized cognitive results, and the POI categories could be further refined, such as distinguishing department stores and various theme emporiums, to carry out the public cognition survey in more detail. In addition, when executing the spatial clustering and attribute normalizing, as the selection of x and *Minpts* and the classification of the clustering results and characteristic attribute are influential to the final calculation results, the most suitable clustering parameters and grading criteria should be determined after several experiments.

The hierarchical landmarks extracted from POIs with different significances can reflect hierarchical regional spatial knowledge, and further be used in intelligent navigation systems. In route directions, a sequence of landmarks which are most relevant to the real-time locations of the user can be selected from the landmarks which are found known to her by means of human-computer interaction or machine learning, through measuring their cognitive efforts and cognitive effects. If the neighborhood of the destination is gradually concretized by those sequential landmarks, the navigation system can flexibly and efficiently instruct the user to approach the destination through describing or depicting the landmarks with natural language or schematic map. When the influence area of the landmark with the greatest cognitive effect is arrived, if the accurate location of the destination is still undetermined to the user, the left route should be described turn by turn to guide the user to reach the destination. In specific applications, the destination and the landmarks may be distributed in more complicated manner on a route. Whatever, the navigation process will always conform to human cognition and behavior rules, through combining the destination-based route directions and turn-by-turn route directions, to make the navigation system more humanized and intelligent, such as the route instructions of passengers to taxi drivers.

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利用城市POI数据提取分层地标

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摘　要：为了获取能够用于智能化路径引导的层次性空间知识，提出了一种依据显著度的差异从城市POI数据中提取出分层地标的方法。首先，通过从公众认知、空间分布和个体特征3个方面分析影响POI显著性的因素，构造了包括公众认知度、城市中心度和特征属性值3个指标向量的POI显著性度量模型；然后，分别讨论了利用问卷调查、多密度空间聚类和数据规格化的方法计算POI对象的各项显著性指标值的过程；最后，选择武汉市武昌地区的POI数据进行显著度计算，从中提取显著度较高的对象构成若干层地标，并以各层地标为种子生成加权的Voronoi图，用来反映各地标的空间影响范围并建立了同层和上下层地标之间蕴含的关系。

关键词：导航，空间知识，地标，POI，分层

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1　引　言

导航系统的路径引导由两个基本过程组成：描述路径中的决策点的位置，并说明在决策点处采取的行动(Daniel 和 Denis，1998)。当用户对环境完全陌生时，系统必须依次说明路径中的每个决策点和行动，或对其进行一定程度的归纳(Klippel 等，2009)；当用户有一定环境熟识度时，系统则只需由粗及细地描述路径上显著目标的位置，就能指导其接近目的地(Tomko 和 Winter，2009)。将这两种模式结合起来，使路径引导更加智能且符合人们的认知规律，是新一代导航系统的发展方向。

实现这种导航机制需要建立符合公众印象的、具有层次性的空间知识结构，并在其基础上进行时空关联推理。Lynch (1960)将人们意象中的城市划分为五种基本要素，即道路(Path)、结点(Node)、地标(Landmark)、区域(District)和边沿(Edge)，用来反映人们对活动环境的认知结果。后来有学者提出，城市中的任何要素，只要足够显著，都可以被看作地标(Raubal 和 Winter，2002)。本文采纳Lynch的观点，仍将地标看作点状的、或可以被抽象的为点的空间要素。Siegel 和 White (1975)研究了人类空间认知的过程，指出地标知识是空间知识的基础，且其在一维和二维方向上的集成形成了人们关于环境的构造和布局的知识。地标的显著性特征使其具有明显的区域指代特征，且其显著程度决定了指代区域的范围(Kettani 和Moulin，1999)。Winter等人(2008)等按照显著性对地标进行了分层，并用Voronoi多边形反映其指代区域，进而应用到对空间位置和路径的描述。

从环境中提取合适的地标是空间认知领域的一个研究热点。依据Sorrows和Hirtle (1999)提出的地标具有的3方面特性，即视觉、结构和语义显著性，

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一些学者提出和发展了由这3项指标构成的显著性度量模型，用来计算空间对象的显著度，以判断其是否适合作为地标(Raubal和Winter，2002；Nothegger 等，2004；Klippel和Winter，2005)。Caduff和Timpf (2008)提出了一种更加复杂的显著性度量模型，其中包括感知(Perceptual)、认知(Cognitive)和场景(Contextual)3种显著性向量和一系列成员变量，并利用贝叶斯网络刻画模型中空间对象、观察者和环境的之间的因果关系。Elias (2003)采用两种数据挖掘方法，即基于ID3分类算法和基于Cobweb的聚类算法，从空间数据库中自动提取地标。但是，由于需要对每个空间对象采集大量繁琐且难以维护的指标数据，如外观特征、语义特征、结构特征，甚至包括观察者的认知特征以及应用的场景特征等，并进行复杂的计算和参数设置，以上方法的可实施性较差，难以得到广泛的应用。还有学者研究了利用互联网从各种电子文档资源中搜索与人们进行地理区域描述相关的文本信息，并从中挖掘具有空间场景意义的地标的方法(Tomko，2004；Tezuka和Tanaka，2005)。但是在由于需要处理海量的数据，且难以对目标进行准确的空间定位，这种方法实现起来仍然比较困难。

为了使地标提取更易于实现，本文提出了一种利用POI数据在城市环境中提取分层地标的方法。POI即兴趣点，泛指一切可以被抽象为点的地理实体，尤其是与人们生活密切相关的设施，如商场、车站和学校等，是导航电子地图的重要内容(ISO，2004)。城市中所有具有一定区域影响范围的POI都可以被当作地标，而POI的显著程度是进行地标分层的主要依据。本文分析了影响POI显著性的主要因素，讨论了计算POI显著度的方法，并通过实验展示了利用POI的显著度提取分层地标的过程。

2 影响POI显著性的因素

本节主要从公众认知、空间分布和个体特征方面讨论影响POI显著性的3个因素，分别为公众认知度、城市中心度和特征属性值，并在此基础上提出一个POI显著性度量模型。

2.1 公众认知

在与环境的交互过程中，人们通常把空间知识归纳为一系列类型，完成对现实世界的认知(Mennis 等，2000)。尽管每个人的认知能力和认知结果不尽相同，但通过大量的调查能够发现同类人群共同拥有的知识，从而促进人们对环境的理解和交流(Lynch，1960)。因此，通过广泛的调查能够发现大众对各类POI显著性的认识，即公众认知度。

尽管每个POI都有一定的影响范围和关注人群，但是有些类型的POI分布比较密集且公众认知度很低(如便利店和小餐馆)不适宜作为城市中的显著地标。因此，本文主要讨论可能被多数市民熟知的、具有重要功能和较大规模的POI，如火车站和百货商场，并对其进行公众认知度调查。本文将这样的POI划分为11种类型，并定义了各类POI的基本选取范畴(表1)。

表1 本文研究的POI类型

类型	解释说明
大型商场	百货商场、主题商场和大型超市等
高级酒店	二星级以上酒店和大型餐饮酒店
交通枢纽	车站、机场和港口等
城市公园	综合公园、专类公园和广场等
名胜古迹	著名景观、古迹和纪念馆等
休闲场馆	体育场、剧院和电影院等
重要机关	区委、区政府及以上各级国家机关
文化教育	高等院校、文化馆、博物馆和展览馆等
医院	国家一级以上综合医院及专业医院
大厦	大型写字楼和商务楼等
小区	居民小区和住宅小区

2.2 空间分布

作为城市中商业、服务业以及公共设施等的集中地，城市中心区具有高度的可及性，并对人们的各种活动具有较强的吸引力(Lynch，1984)。因此，城市中心区内的POI容易被大众认知，也具有更高的显著度。每个城市通常包含多个层次的中心区，其中最主要的中心区几乎包含所有最高的、最密集的或最特殊化的行为，次要的中心区则包括次重要、次密集或次特殊化的行为(Lynch，1984)。因此，通过多密度空间聚类能够反映位于不同城市中心区的POI的显著度，即城市中心度。

POI数据的空间分布密度能够反映不同层次的城市中心区：密度最高的POI聚集区通常表示城市中最主要的中心区；密度较低的POI聚集区通常表示较次要的城市中心区。通过多密度空间聚类发现的POI聚集区之间通常存在嵌套关系(图1)。在此例中，由于密度的差异，圆形区域A包含的POI对象的城市中心度要比环形区域B内POI对象的中心度高。

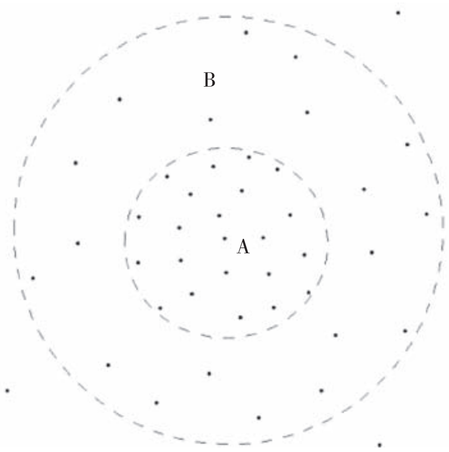


图1　不同层次的POI聚集区

2.3　个体特征

地标的显著性主要体现为其在外观、结构或语义等方面相对于周边环境中其他空间对象的差异，具体包括形状、大小、位置、角色和文化内涵等内容(Sorrows和Hirtle，1999；Nothegger 等，2004；Klippel和Winter，2005)。POI对象在语义和结构方面的显著性主要受其类型和空间分布的影响，可以分别由其公众认知度和城市中心度的差异体现出来；而其在外观方面的显著性则主要取决于其个体特征的差异，如规模的大小或等级的高低。因此，通过采集和比较其特征属性可以反映POI在个体特征方面的显著性差异。

表示POI特征属性的变量可以采取间隔量表，如商场的营业面积，也可以采取定序量表，如酒店的星级。为了消除属性数据的量纲并实现定量与定性数值的混合应用，需要对POI的特征属性数据进行规格化处理，即将采用各种度量方法的原始数据都变换到相同区间内，以用统一的方式反映不同类型POI对象之间的显著性差异。

2.4　POI显著性度量模型

综上，将POI的公众认知度(记为Cog.)、城市中心度(记为Cen.)和特征属性值(记为Char.)综合起来能够全面地反映其显著度(记为Sig.)。因此，本文提出一个由这些指标构成的POI显著性度量模型：

$$\text{Sig.} = c_1 \times \text{Cog.} + c_2 \times \text{Cen.} + c_3 \times \text{Char.}$$

式中，各向量的权重系数c_1、c_2、c_3的和为1。为了消除度量方法的差异产生的影响，式中3个指标向量的值都需要经过规格化处理，以使其取值区间都为[0，1]。权重系数的设定通常需要结合具体的实验结果来进行，以使各POI对象的显著次序基本符合大众的空间认知结果。此外，还可以对已确定的权重系数进行适当的修正，以照顾不同用户群体在偏好、认知习惯、生活环境等方面的差异。

3　POI显著度的计算

以上一节提出的POI显著性度量模型为基础，本节详细介绍了分别利用公众认知度问卷调查、多密度空间聚类以及特征属性规格化的方法计算POI对象的各个显著性度量指标的过程，从而得出其整体显著度。

3.1　公众认知度问卷调查

统计调查是人们用来发现公共知识的重要手段(Lynch，1960)。在2.1节定义的11种POI类型的基础上，本文采用问卷调查的方式，以中青年市民为主要调查对象，请受访者根据自身对各类POI作为区域标志物(即地标)的显著程度的理解，分别做出“不显著”、“不太显著”、“一般显著”、“比较显著”或“很显著”的判断。依据李克特五级量表法，这五种度量标准分别被赋以1到5的分值。

本次调查共收回的233份有效问卷，其中受调查者男女比例适中，职业分布广泛，且都大多具有5年以上的城市生活经验。利用SPSS软件对统计数据进行均值和标准差分析，并对各均值进行极差正规化处理就可以获得各类型POI的公众认知度。对其按照均值大小排序可以得出表2所示的结果。

表2　各类POI的公众认知度

POI类型	均值	标准差	公众认知度
交通枢纽	4.4449	0.69148	1.0000
名胜古迹	4.0529	0.87078	0.8245
大型商场	4.0308	0.84870	0.8146
文化教育	3.7093	0.97038	0.6706
城市公园	3.6740	0.88217	0.6548
高级酒店	3.4537	0.93189	0.5562
医院	3.3436	0.88046	0.5069
休闲场馆	3.3304	0.89299	0.5010
重要机关	3.0044	1.04964	0.3550
大厦	2.8943	0.96730	0.3057
小区	2.2115	0.87707	0.0000

根据表2的统计结果可以发现，小区的公众认知度比较低，不适宜作为显著的地标。因此，用来进行地标提取的POI数据库仅需包含其余10种类型的POI。POI数据库中可能存在冗余数据，如同时包含

商场和其所在的大厦，或者位置重叠的机关单位。故在进行下一步操作之前还需要对POI数据库进行预处理，以发现并剔除冗余数据。在此过程中，只需要保留发生冗余现象的POI中公众认知度或特征属性值较高的对象。

3.2 多密度空间聚类

本文采用OPTICS思想对POI数据进行多密度的空间聚类以判断其城市中心度。OPTICS是通过对给定数据集合中的元素进行排序生成层次性聚类结构的一种聚类算法(Ankerst等，1999)。为了便于观察聚类的结果以选择合适的最大聚类半径ε和ε邻域内的最少对象数量(*MinPts*)，本文对传统的OPTICS算法主要进行了处理方式上的改进，将核心距离、可达距离等信息直接记录在数据库中，并指定核心对象和非核心对象之间的隶属关系。该算法可以通过以下5个步骤实现：

(1)初始化数据库

为数据库中的POI数据表添加是否已处理标识、是否核心对象标识、核心距离、可达距离和隶属核心对象等属性字段，将各POI对象标识为未处理，并为其他字段赋缺省值。

(2)建立聚类集合

从每个未处理的并符合核心条件(在半径为ε的邻域内至少包含*MinPts*个对象)的对象开始，将所有密度可达的、未处理的对象组成聚类集合。将集合内所有对象标识为已处理，将其中符合核心条件的对象标识为核心对象，并计算和记录其核心距离。

(3)筛选核心对象

逐对判断聚类集合内任意核心对象之间的实际距离与两者的核心距离之和的关系：如果前者小于或等于后者，则将核心距离较大的对象重新标识为非核心对象，并将其核心距离修改为缺省值；否则，保留两个核心对象及其核心距离。

(4)确定高密度簇

把聚类集合内以核心对象为中心、以核心距离为半径的邻域范围内所有对象定义为高密度簇。将各高密度簇内的所有对象的可达距离记录为该簇的核心距离，并将该簇的核心对象记录为该簇内各个非核心对象的隶属核心对象。

(5)归组剩余对象

对于聚类集合内未确定隶属关系的各个非核心对象，找出集合内距离其最近的核心对象，并计算两者的距离。如果该距离小于ε，则将该核心对象记录为其隶属的核心对象，并该距离记录为其可达距离；否则，视该对象为聚类噪声。

在经过初始化后，依次按照2到5四个步骤遍历整个POI数据库，就能够实现反映了多个密度等级的POI空间聚类。聚类完成后，从小到大设定N个的聚类距离$\varepsilon'_n(\varepsilon' \leqslant \varepsilon, n \leqslant N)$，并查询数据库中可达距离小于等于$\varepsilon'_n$且大于$\varepsilon'_{n-1}$(当$n$大于1时)的对象，就可以将除“噪声”外的所有POI对象划分到N个层次的POI聚集区中。

假定噪声对象的城市中心度为0。从高到低依次为不同密度等级的POI聚集区内的各个POI对象赋以从N到1的等级值，然后并将其线性变换到区间[0，1]内，就能够计算出所有POI对象的城市中心度。

3.3 特征属性规格化

不同类型的POI对象的个体特征属性通常需要采用不同的表达方法。比如商场、公园、各种场馆、大厦等的个体特征可以分别用营业面积、占地面积、建筑面积、层数等定量的指标衡量。尽管可以对这些指标数据进行极差正规化处理，但是由于这种方式受极端值的影响比较大，更合理的方式是先把同类型的POI按照合适的标准划分为若干等级，然后再对各个等级值进行规格化变换。由于相同大类但不同子类的POI对象之间的度量值也可能不具有实际的可比性，如综合公园和城市广场之间就不能简单地通过占地面积比较其显著性，因此还可以对不同子类型的POI采取不同的分级方式。

本文定义的其他类型的POI不需要统计定量的指标就可以对其进行分级。比如，酒店、医院和名胜古迹可以采用统一的国家或行业标准明确地定级，如五星级酒店和三级甲等医院；高等院校和机关单位的规模则可以根据常识性知识划分为若干个等级，如将前者划分成部属、省属、市属公办高校和民办高校等，将后者划为国家级机关、省部级机关、厅局级机关和县处级机关等。

利用不同的标准将各类POI划分成的若干个等级后，将各个等级值线性变换到区间[0，1]内，就能够将各POI对象的个体特征差异统一地反映在相同的计量标准下。

4　实　验

依据2.1节定义的POI选取范畴，本文选择武汉市武昌地区的556个POI进行地标的分层提取实验，其中包含高级酒店119个、大型商场115个、文化教育机构113个、重要机关74个、大厦39个、医院33个、名胜古迹21个、休闲场馆21个、城市公园14个以及交通枢纽7个。

首先，按照3.2节提出的多密度空间聚类算法对这些POI数据进行聚类，其中ε和$MinPts$分别被设为4 km和25个。利用ArcScene软件对聚类结果进行图2所示的可视化，其中柱表示的POI对象的柱体高度与其可达距离成反比，点表示的POI对象为噪音。图中所有POI按照可达距离的大小被自然分割为5组，分别对应5个等级的城市中心区，其中等级最高的为中南片区、街道口片区、司门口片区、光谷片区和徐东片区等，基本符合公众对武昌地区的城市中心区分布现状的认知结果。按照聚类密度从高到低依次为各组POI对象赋以5到1的值，然后将其线性变换到区间[0，1]内，就可以得到各POI对象的城市中心度。

然后，对每个POI对象的特征属性进行规格化处理，并将3.1节确定的各类型POI的公共认知度赋予各个POI对象。由于目前导航数据生产商提供的POI数据中通常不包含特征属性信息，因此本实验主要采取互联网搜索和实地考察相结合的方法统计了各个POI对象的特征属性数据，并按照既有的标准和常识性的知识将各中类型的POI数据划分成若干个等级。为等级较高的POI对象赋予较大的等级值，然后对其进行规格化处理，就可以获取各POI对象的特征属性值。

确定了各POI对象的公众认知度、城市中心度和特征属性值后，利用2.4节提出的POI显著性度量模型并为模型中各向量赋以合适的权重系数，就可以计算出其整体显著度。合适的权重系数需要使POI显著度计算的结果能够被大众广泛接受，并可以在必要时反映特定用户在偏好、认知习惯和生活环境等方面的差异。本实验采取了专家评分法和方式，对采用若干组具有代表性的权重系数得到的计算结果进行合理性分析和比较，最终将公众认知度、城市中心度和特征属性值3项指标向量的权重系数分别设定为0.4、0.2和0.4。表3列举了显著度较高的若干个POI对象的各个显著性度量指标的计算结果以及其整体显著度。为了提高可读性，此表和数据库中的数据记录方式不完全一致。如表3所示，各种类型POI的特征属性都被划分为5个等级，其中酒店、名胜古迹按照现有行业标准定级，商场按照营业面积分级，广场按照占地面积分级，交通枢纽和文化教育机构按照常识性知识分级。

显著度不同的POI对象能够被当作地标反映不同粒度的空间知识。显著度较高的地标通常在城市全局范围具有较大影响力，而显著度较低的地标则通常仅在局部范围具有一定影响力。进行路径引导时，人们通常首先选择显著度较高的地标以减小请求者的认知心力，并在必要时选择显著度较低的地标以使请求者获取较大的认知效果。因此，可以按照显著度的差异将地标组织成层次结构，以供调用者根据特定需求做出合适的选择。值得注意的是，地标的分层不同于行

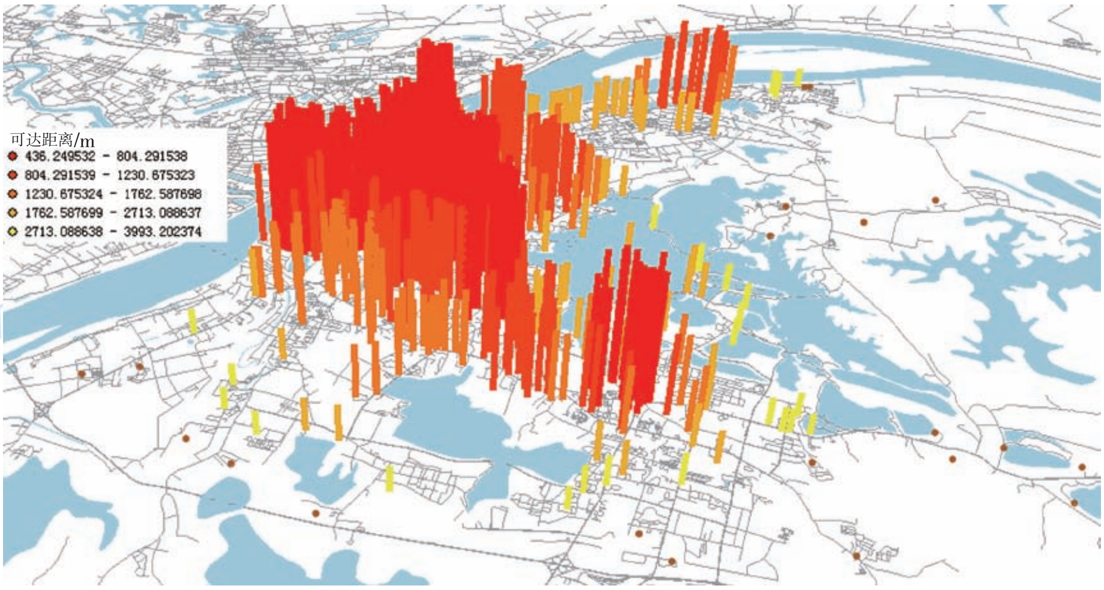


图2　POI数据的多密度空间聚类结果

表3 POI对象的显著度计算结果

编号	名称	特征属性	特征等级	可达距离/m	聚类等级	公众认知度	城市中心度	特征属性值	显著度
1	黄鹤楼	5A景区	5	634.9	5	0.8245	1.0	1.0	0.9298
2	群光广场	9万m^2	5	586.9	5	0.8146	1.0	1.0	0.92584
3	光谷国际广场	6万m^2	5	705.1	5	0.8146	1.0	1.0	0.92584
4	武昌火车站	—	5	1281.5	3	1.0000	0.6	1.0	0.9200
5	销品茂	17.3万m^2	5	838.8	4	0.8146	0.8	1.0	0.88584
6	洪山广场	10.8万m^2	5	436.2	5	0.6548	1.0	1.0	0.86192
7	广埠屯资讯广场	3万m^2	4	586.9	5	0.8146	1.0	0.8	0.84584
8	银泰百货	3万m^2	4	488.0	5	0.8146	1.0	0.8	0.84584
9	中商广场购物中心	3万m^2	4	488.0	5	0.8146	1.0	0.8	0.84584
10	鲁巷广场购物中心	5万m^2	4	705.1	5	0.8146	1.0	0.8	0.84584
11	武汉电脑大世界	3.2万m^2	4	586.9	5	0.8146	1.0	0.8	0.84584
12	大洋百货光谷店	3.3万m^2	4	705.1	5	0.8146	1.0	0.8	0.84584
13	傅家坡汽车客运站	—	3	488.0	5	1.0000	1.0	0.6	0.8400
14	湖北省博物馆	—	5	1074.1	4	0.6706	0.8	1.0	0.82824
15	五月花大酒店	5星级	5	488.0	5	0.5562	1.0	1.0	0.82248

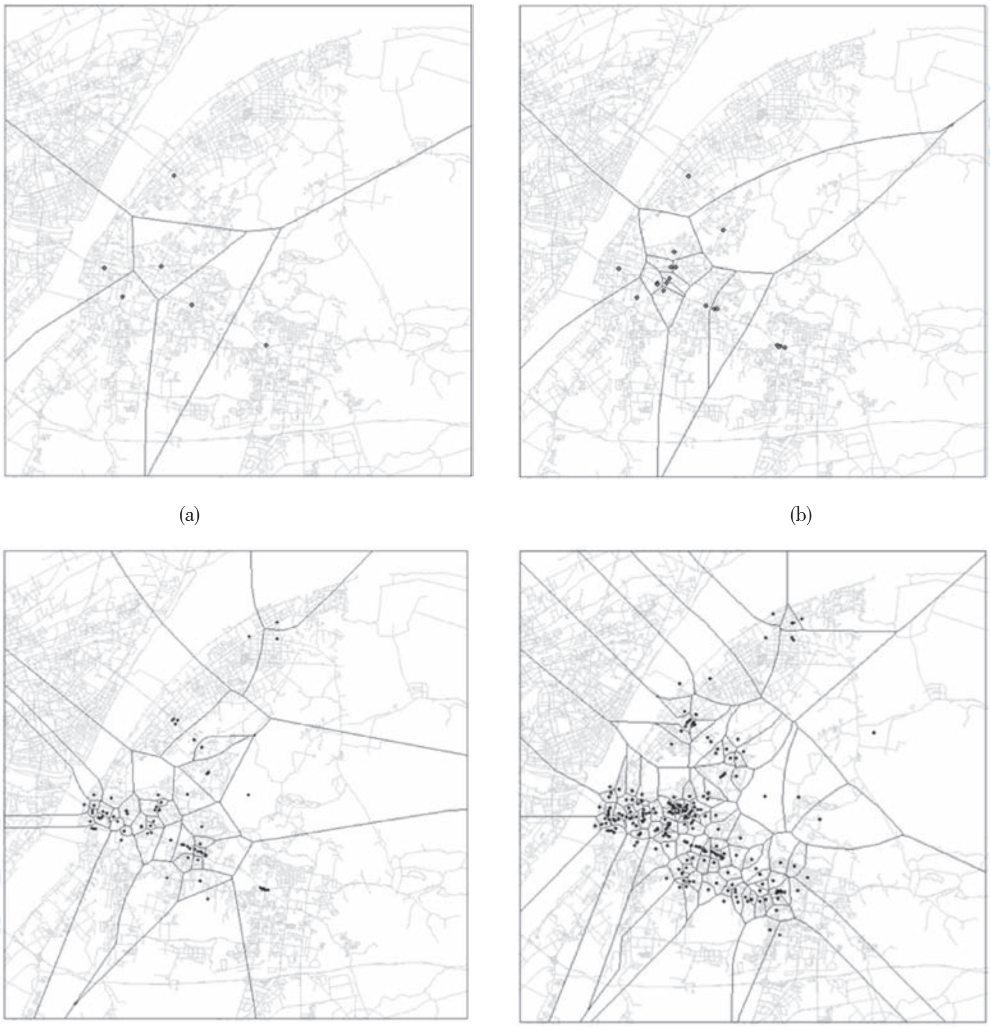
政区的分层，因为高层行政区在低层由于被分割成若干个较小的区域而不复存在，而高层地标仍然需要出现在低层并起不同作用，如黄鹤楼可以作为武汉市的全局地标，也可以被当做局部地标指代其邻近区域。

根据POI显著度的计算结果，本实验分别选取显著度大于0.85、0.82、0.76、0.65和0的 POI对象构成5个层次的地标，其中各层地标的数量分别为6个、19个、69个、223个和556个，并且较高层地标总是较低层地标的子集。在分层结果中，第1层地标为黄鹤楼、光谷国际广场、群光广场、武昌火车站、销品茂和洪山广场；第2层地标除了包含第1层的所有地标外，还包括鲁巷广场购物中心、华美达光谷大酒店、大洋百货光谷店、广埠屯资讯广场、武汉电脑大世界、湖北省博物馆、中商广场购物中心、银泰百货、洪广大酒店、东湖大厦、纽宾凯新时代国际酒店、五月花大酒店和傅家坡汽车客运站等；其他各层地标由于篇幅的限制不在文中一一列举。

由于较显著的地标具有较大的空间影响范围，故以各层地标为种子对空间进行加权的Voronoi剖分能够直观地反映各个地标可以指代的区域，且各种子地标是对应指代区域内最显著的地标。图3展示了利用Dong (2008)提出的加权Voronoi图生成算法对最高4层地标以其显著度为权值进行空间剖分的结果。由于本算法采用栅格法构建Voronoi图，当栅格划分不足够精细时，同一个栅格单元内的要素会共享相同的Voronoi多边形(如本实验中的光谷国际广场、鲁巷广场购物中心、华美达光谷大酒店和大洋百货光谷店)但由于其聚集在较小的空间范围内，故不会对空间分割的合理性产生影响。方形栅格单元的边长由对包含所有输入要素的最小外接矩形的长和宽取最小值，然后除以一个分割份数(此例中被设为250)获得。如果各层地标的覆盖范围有差别，生成Voronoi图时各层栅格划分也不尽相同。当多个地标位于同一个栅格单元内时，选取显著度最高的地标作为该栅格单元的代表地标(当显著度最高的地标有多个时，可以任意选取其中的一个)。

利用各层地标构建的多层Voronoi图可以反映每个地标的认知难度和认知效果。每个地标可以用其能够出现的最高层M以及实际所在的层I两个变量表征，其中$M \leqslant I$。M越小，说明地标的空间影响范围越大，认知难度越小；I越大，说明地标的语境内涵越明确，认知效果越好。在进行路径引导时，确定目标所在的最低层的Voronoi多边形后，该多边形的种子地标就具有最好的认知效果。如果该地标的M值为1，则其还具有最小的认知难度，只介绍该地标请求者就可能明白目标的大概位置；否则，还需要借助上下层地标之间的语境包含关系发现并说明其他M值更小的地标，以尽量减小请求者的认知心力。由于每个地标所属Voronoi多边形的大小实际反映了其在当前层次的语境确定程度，因此利用多层Voronoi图中上下层多边形的覆盖关系可以建立上下层地标之间的语境包含关系。多层地标可以形成一个类似树的结构，只是其中有些子结点可能从属于若干个父结点，且有些父结点和子结点表示相同的地标。

利用Voronoi图的对偶的Delaunay三角网还能够建立同层地标之间的邻接关系。用一个合适的数据结构描述同层和上下层地标之间的关系，就可以支持符合人们的空间认知规律的区域性空间知识的表达和推



(a)　(b)　(c)　(d)

图3　从POI数据中提取的分层地标

(a) 第1层地标(Sig. > 0.85)；(b) 第2层地标(Sig. > 0.82)；(c) 第3层地标(Sig. > 0.76)；(d) 第4层地标(Sig. > 0.65)

理。比如在导航应用中，交互地从该数据结构中发现用户知晓的地标后，利用合适的规则推理出接近目的地、且与实时位置关联度最高的一系列地标，并将其准确地描述给用户，就能够实现简洁、灵活和高效的路径引导。

5　结　论

本文提出的POI显著性度量要素，即公众认知、空间分布和个体特征，能够全面衡量POI对象在语义、结构和外观方面的显著性。虽然特定的场景和用户的空间认知能力等一定程度上也影响了POI的显著性判断，但由于其可变性和主观性较强，不符合构建公共空间知识的主旨，故本文未予考虑。对于POI显著性度量模型，通过为各个向量赋合适的权重系数，可以使计算结果基本符合公众对各POI对象的显著度认知。较合理的权重确定方法是专家评分法：首先选若干有代表性的权值组合方式进行POI显著度计算，然后邀请若干专家凭借经验对计算结果评分，最后选择平均得分最高的一组权值作为模型的缺省系数。此外，为了照顾不同用户群体在偏好、认知习惯和生活环境等方面的差异，还可以对缺省权重系数进行修正，以适应不同应用场合，如通过放大某类型POI的公众认知度系数以提高所有该类型POI对象的显著度。

与传统的针对个体空间要素采集几何、语义等数据以进行显著度评估的方法相比，本文的POI显著度计算方法分别以POI的类型、空间分布和特征属性对考察指标，数据的采集、处理和更新易于实现，具有较好的计算效率、实用性和易操作性。为了使通过调查获得的POI公众认知度结果更通用，本文在样本

抽样时尽量使受访者在性别、年龄、职业和城市生活年限等方面均衡分布。但是，在实际应用中，可以对不同目标群体的认知差异进行严格区分，如女性、老人和教师等，以获取有针对性的认知结果；并可以对POI的分类进一步细化，如区分综合商场和各类主题商场，以进行更详细的认知度调查。此外，在对POI数据进行空间聚类和属性规格化时，ε和$MinPts$的选择、聚类结果和特征属性的分级等都会对最终计算结果产生影响，因此也需要在若干次实验后选择最合适的聚类参数和等级划分标准。

依据显著度差异从POI数据中提取的分层地标可以反映层次性区域空间知识，进而被应用到智能导航系统。利用人机交互或机器学习的方式发现用户知晓的地标集后，在路径引导时，通过衡量其认知难度和认知效果，就可以从中选择与用户实时位置关联度最高的一系列地标。如果这些地标能够越来越明确地表示目的地的邻域范围，利用自然语言或示意图将其描述或描绘出来，就可以灵活、高效地指导用户接近目的地。抵达认知效果最好地标的影响范围后，如果用户尚无法确定目的地的准确位置，导航系统才需要采用基于转向的方式引导用户抵达目的地。在具体应用中，目的地和地标还可能存在更加复杂的分布情况，但是通过组合基于目标和基于转向这两种路径引导方式，总能够使导航过程符合人类的认知和行为规律(如乘客为出租车司机指路的方式) 从而使导航系统更加人性化和智能化。

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