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URBAN FUNCTIONAL ZONE IDENTIFICATION BY CONSIDERING THE HETEROGENEOUS DISTRIBUTION OF POINTS OF INTERESTS

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ABSTRACT:

Urban Functional Zone (UFZ) identification facilitates the understanding of urban systems, which are complex and huge, and helps promote sustainable urban development. Existing studies on UFZ identification with Points of Interests (POIs) have focused much on more accurately extracting functional semantics, but ignored the fine delineation of UFZs in the spatial domain. The fine delineation of the spatial units of UFZs is also a key issue in UFZ identification. Since the sizes of UFZs can be different in practice, it is difficult to delineate spatially heterogeneous UFZs on a fixed scale. To solve the issue, a novel multi-scale spatial segmentation method was proposed in this study. Through taking the homogeneous socio-economic attributes of UFZs into account, we firstly generated a number of multi-scale spatial units by computing the mixed degree of POIs types, which reflects the mixed functions of each UFZs, using information entropy. Subsequently, we constructed the urban functional corpus of each spatial unit by measuring the spatial distribution pattern of POIs. The Word2Vec model was employed to obtain the semantic embedding vectors of UFZs, following which we adopted cosine distance-based K-means clustering method to group similar UFZs into one cluster. Finally, the enrichment factor was used to help annotate each functional cluster with a specific label. The UFZ identification results were compared with the Baidu e-maps and Baidu street view images for evaluation, and an accuracy of 82.7% was obtained. This study considering the heterogeneous distribution of POIs supports the fine-grained identification of UFZs, providing reference for urban planning.

1. INTRODUCTION

Urban Functional Zones (UFZs) refers to the basic zones that carry different socioeconomic activities, e.g., commerce, industry, residence and park (Huang et al., 2021; Zhang, Du, & Wang, 2018). Identifying UFZs in appropriate spatial scale is conducive for further understanding of the city, which refers to a complex giant system, supporting the timely adjustment of urban planning and related policies, and promoting the coupling of man-land system and the sustainable development of the city (Feng et al., 2019; Huang & Wang, 2019; Sun et al., 2013; Yu et al., 2021; Zhang et al., 2021).

Points of interests (POIs) data carries rich semantic information, representing regional and functional land use patterns, which has been widely utilized for UFZ identification (Hu et al., 2020; Yao et al., 2017; Zhang et al., 2020). However, the potentially rich semantics of POIs applied to UFZ identification studies require more effective data mining techniques. Natural language processing (NLP) techniques can reveal the implicit semantics of POIs and are therefore widely used to identify UFZs. For instance, TF-IDF and LDA models were introduced to infer UFZs based on the frequencies of various types of POIs (Du et al., 2020; Gao et al., 2017; Liu et al., 2017; Song et al., 2021). The above approaches only consider the quantitative features of POIs but ignore the important contextual information of POIs. To solve this problem, a number of studies adopted word embedding models to mine the spatial relationship of POIs, achieving more reasonable UFZ identification results (Hu et al., 2020; Liu et al., 2020; Niu & Silva, 2021; Sun et al., 2021; Yao et al., 2017).

However, those studies place more focus on identifying UFZs from the semantic perspective at a fixed spatial scale. Normally, the selection of different spatial scales indicates the heterogeneity of UFZs (Zhang, Du, Wang, et al., 2018), which is a critical feature for UFZ identification but has been less considered in exiting studies.

Existing multi-scale segmentation methods adopted in UFZ identification-related studies attempt to implement different scales of spatial segmentation from high-resolution remote sensing images based on their physical features, such as spectral features and texture features (Du et al., 2019; Zhang, Du, Wang, et al., 2018). They resulted in inaccurate UFZ identification as dealing with the UFZs with similar spectral features, such as campuses and residential areas.

To address the above-mentioned problems, this study proposes a novel multi-scale spatial segmentation method to generate spatial units for identifying UFZs based on POI data and Word2Vec model. The proposed method aims at reducing the heterogeneity of socioeconomic attributes of UFZs units as well as improving the accuracy of functional semantic recognition by adopting NLP techniques. This study aids the fine-grained identification of UFZs.

2. STUDY AREA AND DATA DESCRIPTION

Beijing is the political, scientific, educational, and cultural center of China, and one of the most economically developed regions in China. This study takes the area that is within the fifth ring road of Beijing as the research area (Fig. 1), covering an area of 302

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km^2. The urban structure in this area is complex and functional differentiation is obvious, including a variety of typical land use types, ranging from commercial, industrial to residential land.

The research data is POI data in 2018, obtained through the application program interface (API) of Amap (https://lbs.amap.com/), which has been compiled from multiple data sources and crowdsourced data. POI data can effectively identifying UFZs. Each POI has several attributes, including names, geographic coordinates, address details, and three levels of types, i.e., top-level, mid-level, and sub-level. These spatial and semantic attributes is useful for urban planners to assess urban functional zones (Andrade et al., 2020; Barlacchi et al., 2020). The raw POI data were de-duplicated and the POI data with low public awareness (such as telephone booths and public toilets) were eliminated to ensure the effectiveness. Ultimately, more than 240,000 POIs with three levels of classification are obtained. Figure 1 illustrates the POIs at different scales as well as the heat map of POIs in the study area.

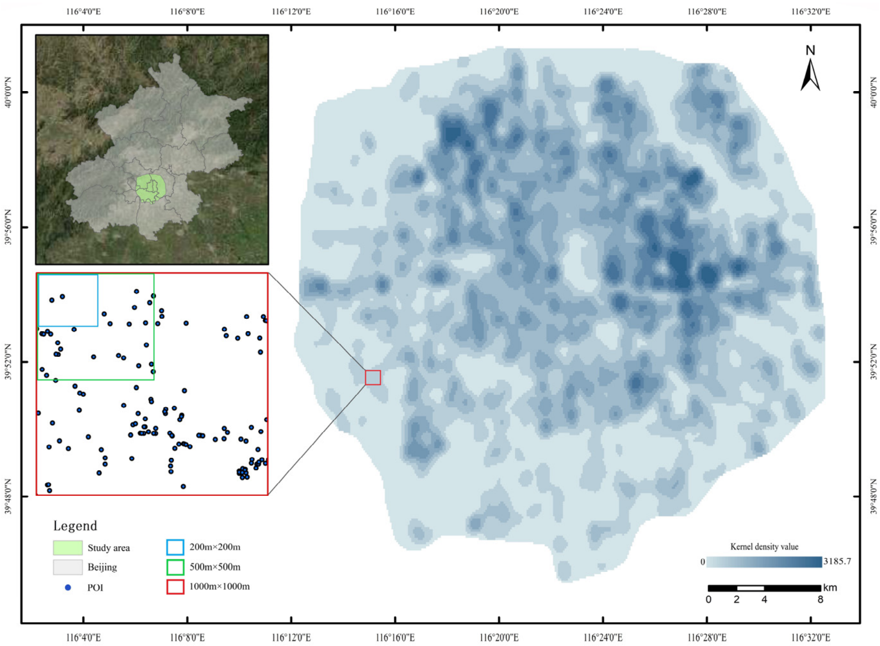

Figure 1. Overview of the study area. The distribution of POIs and POIs at different scales.

3. METHODOLOGY

3.1 Multi-scale Segmentation

In this work, a multi-scale spatial segmentation method was proposed to identify UFZs. Normally, each UFZ is supposed to hold the maximum homogeneity in socio-economic attributes, which acts as the smallest unit to carry out functional zone analysis. A number of homogeneous grids were used to divide urban geographic space to represent UFZs (Cai et al., 2019; Cui et al., 2020; Tu et al., 2017; Zhang et al., 2019). However, due to the spatial heterogeneity of UFZs (Zhang, Du, Wang, et al., 2018), the actual size of UFZs varies, e.g., the commercial zone in a local region is likely to be smaller than the industrial area, and the size of the commercial zone in different regions may also be different. Therefore, segmentizing urban areas with the same spatial granularity is difficult to adapt to the spatial heterogeneity of UFZs, leading to either under-segmentation or over-segmentation. Aligning with the above-mentioned idea that each segmented spatial unit with homogeneous socio-economic attributes (e.g., a UFZ) is proposed for UFZ analysis, the under-segmentation indicates that the segmented spatial units consist of two or more UFZs rather than a single UFZ, while the over-segmentation means that the segmented spatial units are too small to enclose a complete UFZ. Consequently, starting from the idea of homogeneity of social and economic attributes in UFZs, this study divides urban area into multi-scale spatial units with flexible adaptation.

In order to obtain multi-scale spatial units, we used ArcGIS fishnet tool to generate grids of different sizes. Firstly, we roughly segmented the urban area into a number of large-size grids. POI-based information entropy of each spatial unit was calculated to extract those units with high heterogeneity, which were further segmented to achieve multi-scale spatial segmentation. The overall workflow of multi-scale UFZ segmentation is shown in Figure 2.

Information entropy measures the information transmitted when a specific event occurs. For a system, the more chaotic the system is, the higher the information entropy will be (Shannon, 1948). Similarly, for a functional zone, the stronger the functions mix, the greater the entropy of the information.

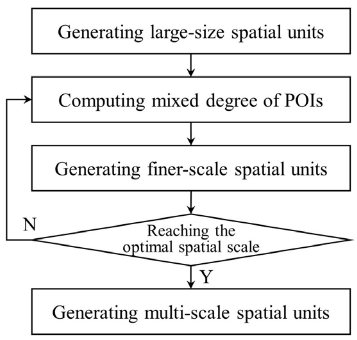

Figure 2. The overall workflow of multi-scale UFZ segmentation.

Thus, information entropy was selected to measure the mixed degree of UFZs, namely the degree of mixing social and economic attributes that are shaped by POI types within each spatial unit (Dovey and Pafka, 2017). The information entropy is defined as follows:

$$H(x) = -\sum_{i=1}^{n} p(x_i) log p(x_i) \quad (1)$$

where $H(x)$ refers to the information entropy of UFZ x, $p(x_i)$ refers to the occurrence probability of POI type i in UFZ x, and n is the total number of POI types.

In this study, information entropy is used to analyse the mixed use of coarse segmented large-size spatial grids to measure the degree of social and economic heterogeneity within each grid. Since each spatial unit used for UFZ identification is supposed to be homogenous in socio-economic attributes, spatial units with high mixed degree are considered under-segmented. Through investigating the statistical characteristics of information entropy distribution, we determined the segmentation threshold parameters, based on which the under-segmentation units were iteratively refined until reaching the optimal level. As a result, a set of multi-scale spatial units were obtained.

The multi-scale segmentation of spatial units follows a hierarchical structure, as shown in Figure 3. The black dot lines represent the relationship between layers, and the red area refers to the under-segmented units with high mixed degree of POIs that need finer segmentation.

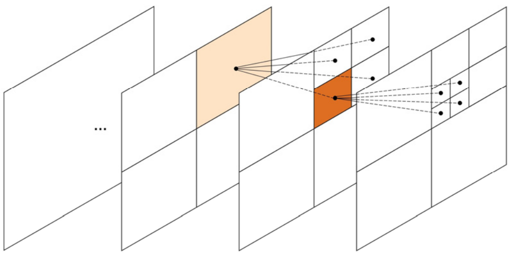

Figure 3. The hierarchical structure of multi-scale segmentation.

3.2 Identifying Urban Functional Zones

UFZ identification includes three steps: constructing urban functional corpus with POIs, computing feature vectors for each UFZ, and labeling urban functional zones, which are described below.

3.2.1 Constructing urban functional corpus with POIs

Corpus refers to the set of texts reasonably processed by natural language processing (NLP) technology (Ng and Zelle, 1997). Since POIs obey a power-law distribution that is similar to natural language (Niu and Silva, 2021; Yan et al., 2017), NLP methods are able to mine the semantic information hidden in POIs. Based on the idea of analogy (Yuan et al., 2012), this study treated the study area as the urban functional corpus, where UFZ and POI types contained in the UFZs were regarded as documents and words in documents. Meanwhile, the spatial distribution patterns among POIs were regarded as the contextual relationship of words in the corpus. We determined the sequential relationship of POIs (i.e., building the context for each POI) according to the Euclidean distance between the centroid of each UFZ unit and the POIs within the unit in geographical space, and builds the whole urban functional corpus by referring to Sun et al. (2021). As illustrated in Figure 4, the centroid of the spatial grid was taken as the sampling point, and the sequence of POIs corresponding to the ***i-th*** grid was sampled according to the distance between the sampling point and other POIs, i.e., the text set of the ***i-th*** document is $Doc_i = \{p_{i,1}, p_{i,2}, p_{i,3}\}$.

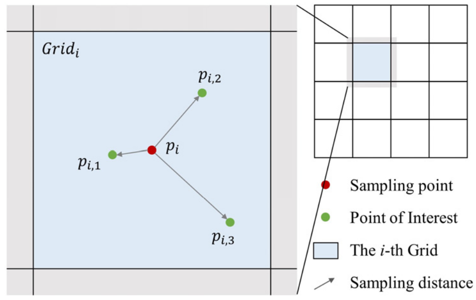

Figure 4. The ***i-th*** document construction of urban functional corpus.

3.2.2 Computing feature vectors for each UFZ

The Word2Vec model (Mikolov et al., 2013) can embed the implied functional semantics of POI data into the high-dimensional semantic space (Yao et al., 2017). Word2Vec includes two neural network structures, Continuous Bag-of-Words (CBOW) and Skip-Gram. In this study, CBOW was applied to train the urban functional corpus. The objective of the CBOW model is to maximize the average log probability to predict the central word in a given context (see Equation 2).

$$L(\theta) = \frac{1}{T}\sum_{t=1}^{T} \log\ p(w_t|w_{t-c}^{t+c}) \quad (2)$$

where T refers to the size of the urban functional corpus. w_t is the ***i-th*** central word, w_{t-c}^{t+c} is a context word set obtained based on w_t and the sampling window c.

The conditional probabilities $p(w_t|w_{t-c}^{t+c})$ is defined using the SoftMax function as follows:

$$p(w_t|w_c) = \frac{\exp\left(-E(w_t, w_{t-c}^{t+c})\right)}{\sum_{i=1}^{T} \exp\left(-E(w_t, w_{t-c}^{t+c})\right)} \quad (3)$$

where E is an energy function and is calculated with $E(w_i, w_j) = -(w_i, w_j)$.

In this way, the CBOW-based Word2Vec model can learn the embedding vectors $POI\_Embedding_i$ of ***i-th*** type POI. The functional semantics of ***j-th*** UFZ is characterized by the feature vector $UFZ\_Embedding_j$, which is computed as follows:

$$UFZ\_Embedding_j = \frac{\sum_{i=1}^{N} POI\_Embedding_{i,j}}{N} \quad (4)$$

where $POI\_Embedding_{i,j}$ refers to the embedding vector of ***i-th*** type POI in ***j-th*** UFZ, N is the number of POIs in ***j-th*** UFZ.

3.2.3 Annotating urban functional zones

In order to obtain the specific functions of UFZs embedded in the above-extracted feature vectors, we further did annotation through grouping those feature vectors into K functional clusters based on their semantic distance. Considering the high dimension of feature vectors, cosine similarity was selected to measure the semantic similarity between feature vectors of different clusters representing different categories of UFZs. The cosine similarity is defined as follows:

$$CosSim(X,Y) = \frac{X \cdot Y}{\|X\|\|Y\|} = \frac{\sum_{i=1}^{n} X_i Y_i}{\sqrt{\sum_{i=1}^{n} X_i^2}\sqrt{\sum_{i=1}^{n} Y_i^2}} \quad (5)$$

where X_i, Y_i refer their corresponding UFZ feature vectors, respectively.

Subsequently, cosine similarity-based K-means was used to aggregate adjacent UFZ feature vectors in semantic space. As the prior parameter of the K-means algorithm, the K value affects the clustering result. We adopted two methods, namely the average silhouette coefficient method and elbow method, as the criteria to determine the optimal K value for the cluster number. The higher the silhouette coefficient is, the better the clustering effect is. With regard to the elbow method, the k value corresponds to the elbow curve is the best value.

A UFZ cluster indicates the enclosed UFZs have similar urban functional semantics and are divided into the same functional category. However, unsupervised clustering algorithm cannot get the actual semantics of the categories belonging to each functional zone. Enrichment factor indicates the percentile of one term among all terms, which has been widely used in the geology filed. In this work, we used enrichment factor to compute the proportion of POI types in a spatial unit, helping infer and label the abundant semantics of each category, which has been adopted as a popular annotation approach in some previous studies (Niu and Silva, 2021; Zhai et al., 2019). The enrichment factor can be calculated by the following formula:

$$EF_i^q = (N_i^q / N_i)/(N^q / N) \quad (6)$$

where EF_i^q denotes the enrichment factor of q-type POI in functional category i, N_i^q is the number of q-type POI in functional category i, N_i is the total number of POIs in functional category i, N^q is the total number of POIs in functional category i, and N is the total number of all POIs.

4. RESULTS

This study used Python version 3.6 and ArcGIS version 10.2 on Windows 10 (×64) to implement the experiment. ArcGIS was used for geoprocessing. Genism library for Python (https://radimrehurek.com/gensim/) was used to run the Word2Vec model. Scikit-learn library for Python (https://scikit-learn.org/) was used to conduct machine learning algorithms, e.g., k-means clustering.

4.1 Multi-scale Spatial Units

With respect to the multi-scale segmentation method, we set three hierarchical structures, which were 1000×1000m, 500×500m, and 200×200m (Luo et al., 2021). A comparison of different sizes is shown in Figure 1. Firstly, POI data were mapped to the 1000×1000m grids, and the mixed degree at such scale was calculated, as shown in Figure 5 (a). The vertical green line (i.e., the information entropy value of 3.671) corresponds to the statistical feature μ was set as the first-level segmentation threshold (Du et al., 2020). The grids with the mixed degree higher than the threshold of the first level segmentation were divided into two levels to obtain the mixed qualified grids with finer scales of 1000×1000m and 500×500m. Further, the POIs were mapped to them again to calculate the new mixed degree distribution (Fig. 5 (b)). $\mu + \sigma$ (4.366) was set as the second level segmentation parameter (Du et al., 2020). The granularity of the existing mixed spatial grid was further optimized with 200×200m grid. Consequently, a total of 3,005 spatial units mixed with the above-three spatial scales were obtained.

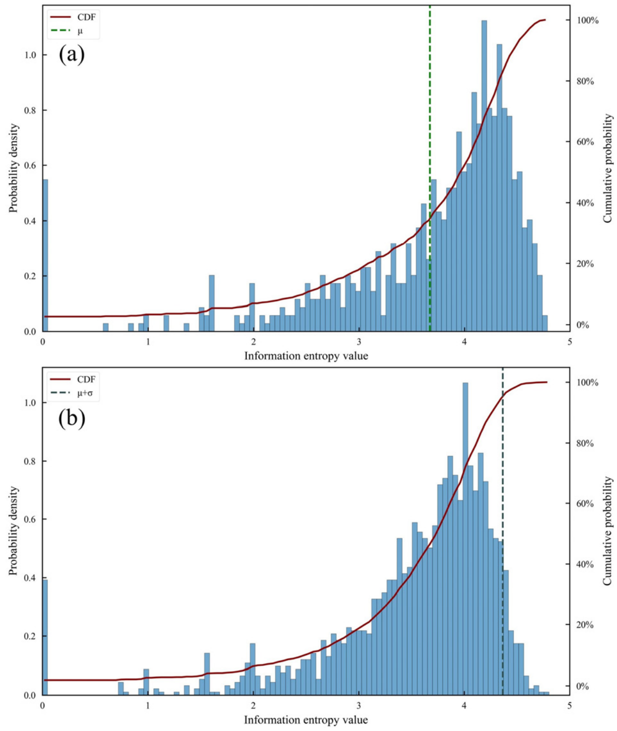

Figure 5. Information entropy distribution at different segmentation levels. (a): First level. (b): Second level.

4.2 Urban Functional Zone Identification

4.2.1 Word2Vec-based UFZ feature extraction

Based on the method introduced in Section 3.2.1, the spatial relationship of POIs was transformed into the context information of words, constructing the urban functional corpus of Word2Vec model. Meaningless POI sequences with dimensions less than 3 in the corpus were eliminated, and spatial units without POI sequences were excluded from the study.

We set the dimension of the output word vectors to 20, the sampling window size to 3, and the number of iterations to 100 based on the default values set by Python library. Through the calculation of Word2Vec model parameters trained in Section 3.3.2, the 20-dimensional word embedding vectors of each mid-level POI type were obtained. Ultimately, 2,761 feature vectors of 3,005 spatial units were obtained through Equation 4, after excluding a total of 244 meaningless spatial units that are not covered by POIs. Each feature vector represents the functional semantics of the corresponding spatial unit.

4.2.2 K means-based UFZ aggregation and annotation

As indicated in Section 3.3.3, the selection of K value directly affects the clustering effect of the K-means algorithm. As such, we set K value from 4-14 to test the clustering effectiveness to determine an optimal K value. We first apply the silhouette coefficient method. As shown in Figure 6 (a), when K is equal to 4, 5, 6, and 7, it returns higher silhouette coefficient values, indicating that the clustering results are more effective. In order to select an optimal K value among the above-mentioned four values, we further apply the elbow method. As shown in Figure 6 (b), it appears an elbow when K equals to 6 (i.e., the point at which the SSE decline plateaus.). As such, we choose 6 as the optimal K value for k-means clustering in this study.

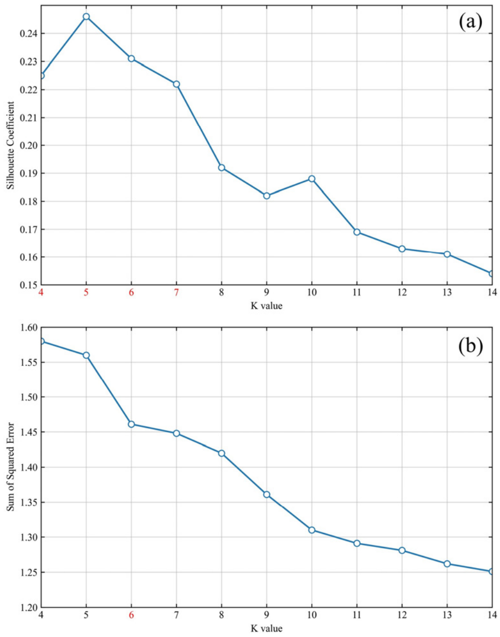

Figure 6. Changes of Clustering effect of different K values. (a): Silhouette coefficient method. (b): Elbow method.

Subsequently, we implemented K-means algorithm (K=6) for the aggregation of 2,761 $UFZ\_Embeddings$ vectors in the study area to obtain the identification result of UFZs, as shown in Figure 7. The category of the $UFZ\_Embeddings$ vector corresponding to each spatial unit was annotated using a specific color and used to represent a category of UFZs. While constructing the urban functional corpus, the spatial units excluded from the study were labeled as white sparse areas.

The enrichment factor (EF) of top 20 mid-level POI types within each cluster and its corresponding internal ranking (IR) are illustrated in Table 1. We annotated these clusters by referring to the Baidu e-maps (https://map.baidu.com/). The labeled six functional clusters are explained in detail as follows.

C0: Industrial zone, rendered in grey color in Figure 7. POIs, including Finance Company, Famous Enterprise, Company, Industrial Park, Factory, etc., hold higher IR, and are aggregated in the C0 category. Thus, the C0 category was annotated as the industrial zone. Most of those UFZs labeled with C0 concentrate around urban fringe, which is consistent with the spatial distribution characteristics of C0. The UFZs belonging to C0 include the CBD business districts etc.

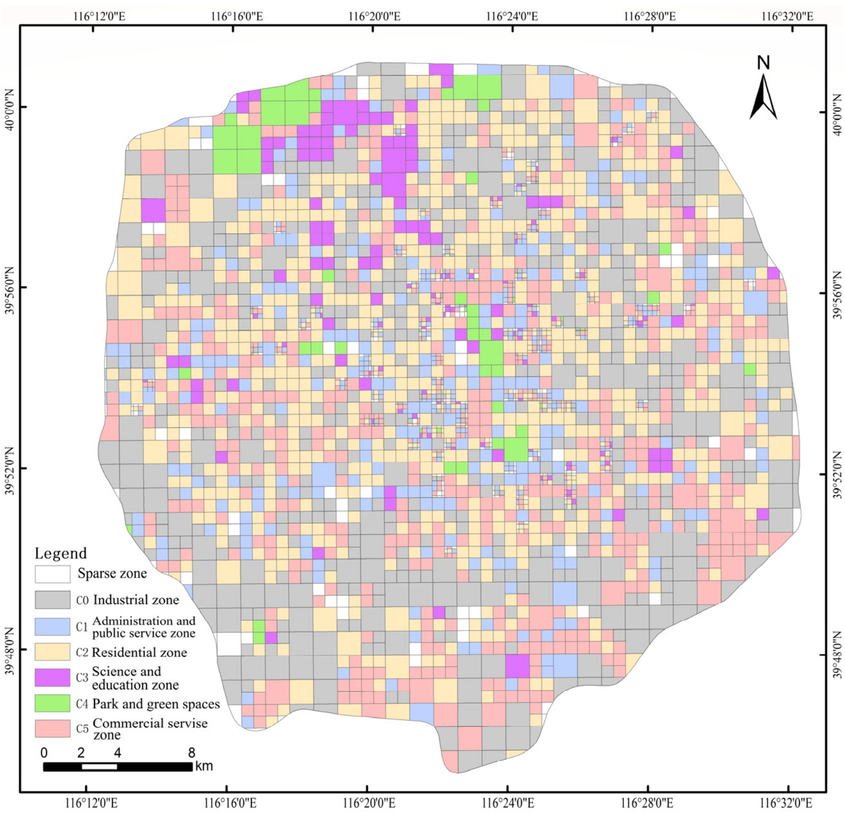

Figure 7. The result of UFZ identification.

C1: Administration and public service zone, rendered in blue color in Figure 7. The EF value of Democratic Party in this zone is the highest (i.e., 8.44). Meanwhile, compared with the other clusters, Governmental Organization, Industrial and Commercial Taxation Institution, Job Center Organization is a unique feature in C1. C1 also includes a number of different types of POIs such as Library, Talent Market and Baby Service Place, which can provide public service in those UFZs. Therefore, this cluster was annotated as the Administrative and public services zone.

C2: Residential zone, rendered in yellow color in Figure 7. It can be seen from Figure 7 that C2 functional zones is evenly distributed in the whole urban compared with other UFZ categories. Among C2 UFZs, various types of POIs of residential services are deployed, including Baby Service Place, Post Offices, Medical and Health Care Service Place, etc. Thus, C2 was annotated as residential zone. Stationary Store ranks the highest in C2. The potential reason is that many residential zones are called school district houses, which are close to primary and secondary schools, contributing to the high enrichment factor of Stationary Store in this cluster.

C3: Science and education zone， rendered in purple color in Figure 7. As can be seen from Figure 7, most of C3 zones are located in the northwest of the research area, which is consistent with the actual distribution of universities in Beijing, e.g., Tsinghua University, Peking University, Beihang University, University of Science and Technology Beijing, Beijing Institute of Technology, and Renmin University of China. Table 1 also demonstrates that the top four POI types that all carry scientific, educational and cultural functions. The higher EF of Disease Prevention Institution lies in the fact that medical schools are often close to hospitals.

C4: Park and green spaces, rendered in green color in Figure 7. The POI type with the highest IF (i.e., 60.87) was scenic spots, which is significantly higher than other types of POIs. Despite that, Tourist Attraction Related, Park & Plaza also holds high IR. POI type of Shopping Related Places ranked third in the cluster, which can be well explained by the fact that Scenery Spot and other places usually co-occur with Shopping Related Places. Typical landmarks in the study area can be identified by this cluster, including Yuanmingyuan, Summer Palace, Olympic Park, Temple of Heaven Park, Taoranting Park, and Beihai Park, etc.

C5: Commercial service zone, rendered in red color in Figure 7. Mixed types of POIs dominate the top EF values in this cluster, e.g., Planetarium, Stationary Store, Information Centre, Democratic Party and Baby Service Place are not functionally synonymous. Meanwhile, a few types of POIs in other categories of functional zones also have high EF value, which are not enough to identify those UFZs in C5 area. Considering that several types of POIs ranked lower in this cluster are unique, such as Home Electronics Hypermarket, Shopping Related Places, Shopping Plaza, and Supermarket, etc. Therefore, C5 was annotated as commercial service area. Besides, the typical commercial zones identified in this cluster include Wangfujing Commercial Street and Xidan Commercial Street, both of which are the most famous commercial zones in Beijing.

To evaluate the accuracy of the whole work, 150 samples were randomly selected (both the spatial distribution and functional categories were random) from 2761 spatial grids with functional area identification results. The Baidu e-maps contains a street view image layer and a high-resolution remote sensing image layer, which can qualitatively determine the type of UFZ of the samples based on human common knowledge. Referring to the Baidu e-maps, we manually labeled the truth value of the sample and compared it with the recognition results, and 82.7% was obtained as the accuracy of this study.

Table 1. The top 20 mid-level POIs and their enrichment factor values. EF: enrichment factor, IR: internal ranking.

	C0		C1		C2		C3		C4		C5	
IR	POI	EF	POI	EF	POI	EF	POI	EF	POI	EF	POI	EF
1	Travel Agency	2.67	Democratic Party	8.44	Stationary Store	6.25	Planetarium	9.16	Scenery Spot	60.87	Planetarium	9.16
2	Ticket Office	2.67	Stationary Store	6.25	Baby Service Place	4.17	School	9.14	Information Center	34.51	Stationary Store	6.25
3	Finance Company	2.22	Job Center	4.17	Travel Agency	2.67	Research Institution	8.46	Shopping Related Places	19.72	Information Center	3.84
4	Famous Enterprise	2.06	Baby Service Place	4.17	Ticket Office	2.67	Archives Hall	7.99	Science & Technology Museum	19.72	Democratic Party	3.45
5	Coffee House	1.78	Governmental Organization	3.67	Plants & Pet Market	2.34	Disease Prevention Institution	7.58	Exhibition Hall	11.07	Baby Service Place	3.41
6	Company	1.64	Industrial and Commercial Taxation Institution	3.64	Planetarium	2.19	Stationary Store	6.25	Planetarium	9.16	Travel Agency	2.67
7	Logistics Service	1.60	Public Security Organization	3.29	Hotel	2.05	Emergency Center	4.72	Daily Life Service Place	8.63	Ticket Office	2.67
8	Finance & Insurance Service Institution	1.55	Cultural Palace	3.28	Bakery	2.05	Convention & Exhibition Center	4.36	Museum	8.12	Hostel	2.56
9	Professional Service Firm	1.53	Social Group	3.26	Dessert House	1.97	Baby Service Place	4.17	Archives Hall	7.99	Personal Care Items Shop	2.56
10	Foreign Organization	1.52	Sports Store	3.13	Job Center	1.64	Library	3.90	Tourist Attraction Related	7.72	Plants & Pet Market	2.34
11	Industrial Park	1.51	Agency	3.13	Accommodation Service Related	1.64	Science & Technology Museum	3.14	Disease Prevention Institution	7.58	Home Electronics Hypermarket	2.27
12	Securities Company	1.48	Traffic Vehicle Management	2.86	Veterinary Hospital	1.39	Travel Agency	2.67	Park & Plaza	6.60	Shopping Related Places	2.20
13	Media Organization	1.43	Travel Agency	2.67	Agency	1.37	Ticket Office	2.67	Stationary Store	6.25	Dessert House	2.05
14	Home Building Materials Market	1.40	Ticket Office	2.67	Foreign Organization	1.33	Museum	2.42	Theatre & Cinema	5.32	Telecom Office	2.02
15	Enterprises	1.40	Governmental & Social Groups Related	2.62	Training Institution	1.31	Scenery Spot	2.36	Baby Service Place	4.17	Chinese Food Restaurant	1.99
16	Farming，Forestry，Animal Husbandry and Fishery Base	1.38	Hostel	2.50	Bank Related	1.29	Plants & Pet Market	2.34	Arts Organization	3.54	Shopping Plaza	1.98
17	Insurance Company	1.34	Library	2.38	Bath & Massage Center	1.27	Hotel	2.05	Democratic Party	3.45	Clothing Store	1.95
18	Stationary Store	1.33	Daily Life Service Place	2.34	Holiday & Nursing Resort	1.26	Bakery	2.05	Art Gallery	3.38	Supermarket	1.92
19	Factory	1.29	Finance Company	2.22	Medical and Health Care Service Place	1.25	Dessert House	1.97	Recreation Place	3.29	Recreation Place	1.91
20	Building	1.23	Holiday & Nursing Resort	2.15	Post Office	1.25	Social Group	1.74	Traffic Vehicle Management	2.94	Convenience Store	1.89

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5. DISCUSSION AND CONCLUSION

Through taking the heterogeneous distribution of POIs, we proposed a multi-scale spatial segmentation method in this study, aiming at reducing the effect of spatial scale effect on UFZ identification. The finely segmented spatial units can help identify fine-grained urban functions. Meanwhile. Word2Vec model was further employed to identify the functional semantics of each UFZ, obtaining an accuracy of 82.7%. The method proposed in this work can be applied to other cities and other sources of POI data (e.g., POIs provided by the OpenStreetMap platform).

Despite the achievements we have made in this study, there still exist certain aspects to be improved. For instance, the three segmentation scales selected for the implementation of the multi-scale segmentation method in this study cannot perfectly fill the actual geospatial space. Moreover, the generation of multi-scale spatial units is related to the selection of initial points. Different initial points may generate different spatial partition results, which affects the UFZ identification results. Randomly selecting a number of initial points to conduct sensitivity analysis rather than using the ArcGIS fishnet tool can be a potential solution to evaluate the robustness of our proposed approach.

In conclusion, the multi-scale spatial segmentation method proposed in this study can detect UFZs of different sizes for fine-grained UFZ identification based on NLP techniques. It should be noted that parameter selection plays an important role in conducting this multi-scale segmentation method. In the future, we will explore the effects of different parameters on the identification of UFZs. The road network features can also be integrated to delineate the morphology of UFZs.

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