HYPERLINKING MECHANISMS IN COMMERCIAL COMPLEX

An Example of The Spatial Network in Taikoo Li Sanlitun, Beijing

SHAOJI WU
[1] *Tianjin University*
[1] *wsjarchitecture@tju.edu.cn*

Abstract. Commercial complexes play an important role in contemporary cities, with elevators, escalators, and other paths on which people do not take natural movement in it. We consider them as spatial hyperlinking paths, which is originated from the web's hyperlinking technology. This paper studies the path network system in Taikoo Li, Sanlitun, Beijing, in three steps. Firstly, The path system is transformed into a network model, and its spatial network distribution is characterized using betweenness centrality. Secondly, a deep learning approach is used to measure the people's flow at the selected 102 observation points. Then a multiple linear regression(MLR) analysis is conducted using the flow data as dependent variable. And there are 7 independent variables in three types, including betweenness centrality C, H1 and H2 that related to spatial hyperlinks, and B1, F1, F2, and F3 that related to floors. Thirdly, analyzing the MLR model.There are two conclusions. First, using multiple independent variables is better than one variable to fit the people's flow distribution using the regression model. Second, escalators have the effect of enhancing people's flow, while elevators have the opposite effect.

Keywords. Spatial Hyperlink; 3D spatial networks; Commercial Complex.

1. Introduction

The concept of spatial hyperlinks is derived from the web's hyperlinking technology, which is an icon, graphic, or text that links to another file or object. Hyperlinks allow web pages to connect to other web pages without knowing their URL. Likewise, we can consider paths that do not use natural movement in buildings, such as elevators and escalators, as spatial hyperlinks. In spatial hyperlinks, pedestrians do not need to move by themselves but "jump" from one space to another with the help of technology. At present, these spatial hyperlinking paths are appearing more and more in our cities.

Today, commercial complexes have become an essential part of cities worldwide and are considered as the prototype of the vertical city in the future. They contain many elevators, escalators, and other paths that create spatial

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hyperlinks from the beginning of construction. This study attempts to address two questions. The first one is how to quantify the effect of spatial hyperlinks on the distribution of people in a commercial complex. And the other is what are the differences between different types of spatial hyperlinks. Answers to the two questions are the research gap this paper hopes to fill.

1.1. RESEARCH REVIEW

Network science is a subject studying network that regards a complex system's main element as its nodes and the relationships between them as edges that we can assign weights. Through the mathematical and statistical study of the network, a holistic understanding of the system can be gained. Space syntax proposed by Bill Hillier(1984) is a network science-based approach using undirected network to analyzing spatial layouts and human activity patterns in buildings and urban areas, based on the natural movement of the human being. This theory has the advantage of simplicity. But it has two drawbacks. The first is that it does not take into account the phenomenon of spatial hyperlinks. The other is that because the edges of the network are all undirected in this theory, there will be some errors when analyzing spatial systems that contain directed paths such as escalators.

Current research on the phenomenon of spatial hyperlinks is mainly in the field of urban studies. Law, Chiaradia, and Schwander(2012) studied London's street network and subway network and found that the two systems fit the reality better when constructed them together. Sheng, Yang, and Hou(2015) researched the subway and street system in Chongqing and concluded that streets around subway stations show a spatial hyperlink effect due to the subway network development.

To address the spatial network within the commercial complexes, Zhang, Zhuang, and Dai(2012) studied three commercial complexes in Shanghai using an axis model based on spatial syntax. Their study compared the significance of individual variables in the regression model and found that local integration(R3) is the most influential factor, followed by vertical transition, entrance, and level. The vertical transition factor represents spatial hyperlinks. However, their study was unable to distinguish the effects of different types of spatial hyperlinking paths on the people's distribution.

1.2. STUDY AREA

Taikoo Li Sanlitun, one of the most prosperous commercial complexes in Beijing, was selected as the case in this study. The building has five floors, one underground and four above ground, and its construction area is 172,000 square meters. As a representative example of the blocking commercial complexes in Beijing. It contains 17 elevators and 29 escalators, making it a suitable place for studying the phenomenon of spatial hyperlinks in this study.

2. Methodology

Three research methods are used in this study. First, transforming the commercial complex's path system to a network model. The second is to output the pedestrian's flow by the "Gate Count" method using a deep learning algorithm. The third is

to calculate a multiple linear regression(MLR) model reflecting spatial hyperlinks under three distance measures, including topological, metric, and angular distance.

2.1. NETWORK MODELING

In a commercial complex, the path system connects all other systems, such as the sale system, service system, etc. Because all the pedestrians' movement in a building depends on the path system and all other systems only provide space for people to stay. Therefore, the path system is chosen as the modeling object in this study. This section is programmed on C sharp in Rhino/Grasshopper. Three questions need to be answered as follows.

First, we have to decide which element in the path system as nodes and which element as edges when constructing a network. There are two modeling ways in Figure 1: The first is the primal representation, which is the simplest. In this representation, we use junctions as nodes and the path between two junctions as edges, which can use both topological distance and metric distance between two paths as edge weight. The second is the dual representation. This representation uses junctions as edges and the path between them as nodes, which can use the topological distance, metric distance, and angular distance between two paths as edge weight. Because this study needs to calculate the network's centrality using angle distance as edge weights, the dual representation method is chosen as the modeling method.

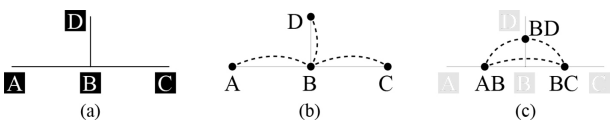


Figure 1. (a) Original spatial network(b) the primal representation (c) the dual representation.

Second, there are two types of spatial hyperlinking paths showed in table 1, i.e., escalators and elevators, and we need identify their characteristics to determine their modeling approach. Escalator is directed paths that pedestrians cannot move in the opposite direction on it. Elevators consist of multiple coupled paths, and if one of them fails, none of the other paths can be used simultaneously.

Third, network science uses centrality to assess the importance of nodes in a network, and we need to decide which centrality to use to characterize the network. This study uses betweenness centrality(BC) to evaluate networks proposed by Freeman (1977). Betweenness centrality is a measure of centrality based on the shortest path, and the value of BC for each node is the number of these shortest paths that pass through the node. It is mathematically defined as follows:

$$BC(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{1}$$

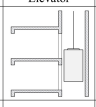
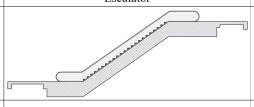
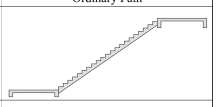
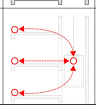
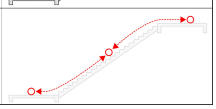
where σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(v)$ is the number of those paths that pass through v. The BC calculated by the above formula is generally large, which results in a small coefficient of BC when calculating MLR model. Therefore, BC is normalized, i.e., all values are mapped

to the interval [0,1], which is calculated as follows:

$$\text{Normalized } BC(v) = \frac{BC(v) - \min(BC)}{\max(BC) - \min(BC)} \tag{2}$$

Figure 2 illustrates three ways of calculating the distance, and we use it as edge weight when building a network. This paper calculates the BC for each node based on these three measures.

Table 1. Network model representation for different types of paths.

Path Type	Coupling Path	Uncoupling Path	
		Directed Path	Undirected Path
Example	Elevator	Escalator	Ordinary Path
Spatial Type			
Network Model			

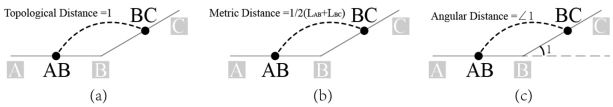


Figure 2. The edge weight using topological(a), metric(b), and angular(c) distance.

2.2. PEDESTRIAN FLOW COUNTING

Traditional pedestrian flow counting methods rely heavily on the researcher's visual inspection, which is the most commonly used method. However, it is impossible to count the precise number of people at an observation point by visual inspection when a large number of people passing through. The deep learning-based Yolo-v3 (You Only Look Once) and DeepSORT (Simple Online And Realtime Tracking With A Deep Association Metric) algorithms are used to calculate the people flow at each observation point to solve the question. In this part, we describe how to use the video taken from an observation point to count of people present in it. This section is programmed on Python by Tensorflow and Keras as the deep learning package and OpenCV as the computer vision package, which can be divided into the following three steps(Figure 3).

First, Yolo-v3 is used for pedestrian detection, which calculates every pedestrian's position and gets the predict boxes in each video frame. Four data $u, v, r,$ and h can be obtained by the predict boxes, where (u, v) are center coordinates of it, r is its area, and h is the aspect ratio. Yolo-v3 is a real-time object detection system proposed by Redmon and Farhadi(2018), and it was selected in this study for the following two reasons. On the one hand, Yolo-v3 can detect objects of various sizes effectively because it uses darknet-53 as its backbone to extract features of the image and can output feature maps at three different scales. On the other hand, Yolo-v3 can derive the predict boxes' coordinates directly

from the image without other steps, which is faster than other algorithms such as Faster-RCNN.

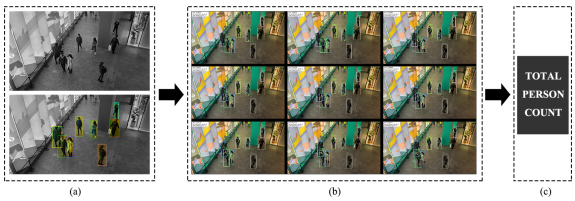


Figure 3. Approach of Pedestrian Flows Counting.

Second, DeepSORT is used for pedestrian tracking to quantify the number of people passing through in the entire video. DeepSORT, proposed by Wojke, Bewley, and Paulus(2017), is an updated version of the SORT algorithm presented in 2016. We use an octave vector $\left(u, v, r, h, \overline{u}, \overline{v}, \overline{r}, \overline{h}\right)$ to represent the trajectory's state of pedestrians at a given moment where $\overline{u}, \overline{v}, \overline{r}$, and $\overline{h}$ are respective velocities of u, v, r, and h between two adjacent frames. SORT only uses the Hungarian algorithm, a combinatorial optimization algorithm that solves the assignment problem and anticipated later primal-dual methods to track pedestrians. Its disadvantage is that the number of identity switches is high when there are obstructions. DeepSORT alleviates this problem by adding cascading classifiers with the Mahalanobis distance and Deep Appearance Descriptor, a small-scale CNN(Convolutional Neural Networks) with 2,800,864 parameters.

The last step is to calculate the pedestrian flow. We obtain the number of pedestrians N_i in a video using Yolo-v3 and DeepSORT, and we also get the duration time T_i of it using OpenCV. The formula is as follows:

$$c = \sum_{i=0}^{n} \frac{N_i}{T_i} \tag{3}$$

where i is the number of videos shot at this observation point, and c is the pedestrian flow count, which unit is *person/min*.

2.3. MULTIPLE LINEAR REGRESSION(MLR) MODEL

Due to the phenomenon of spatial hyperlinking, the distribution of BC does not precisely match the pedestrian distribution in the network. This study addresses this question by establishing the MLR model concerning the research of Zhang, Zhuang, and Dai (2012), and we use it to explain the spatial hyperlinking phenomenon. This section is programmed on Python by Statsmodels package and is divided into the following three steps.

First, a unary linear regression(ULR) model was developed to measure the correlation between pedestrian flow and BC by calculating the coefficient of determination, R-square(R^2). R^2 represents the proportion of variance for a dependent variable explained by an independent variable or variables in a regression model. The larger the R^2, the more reliable the equation.

Second, to quantify the spatial hyperlinking phenomenon, we developed a multiple linear regression(MLR) model. There are seven independent variables selected in this study, which can be divided into three categories. The first one is normalized betweenness centrality(C). The second is related to spatial hyperlinks, which contain two independent variables. Variable H_1 and H_2 respectively represent whether a path is an elevator and escalator, and if a path is an elevator, H_1 is 1, and if a path is an escalator, H_2 is 1. Variable B_1, F_1, F_2, F_3 represent the floor of a path. The model is as follows:

$$N = b_0 + b_1 C + B_2 H_1 + b_3 H_2 + b_4 B_1 + b_5 F_1 + b_6 F_2 + b_7 F_3 + \epsilon \quad (4)$$

where N is the dependent variable representing the people's flow. b_0 to b_7 are the regression coefficients of the independent variables, and ϵ is the residuals.

The third is to test the resulting equation, which can be divided into two steps. We test the reliability of the whole equation by calculating the R^2 and using the F test. And in the F test, we use p values to measure the reliability. The equation holds when the p values are less than 0.05. Another step is to check whether each independent variable is significant through T-tests. The variable holds when the p values are less than 0.05 as well.

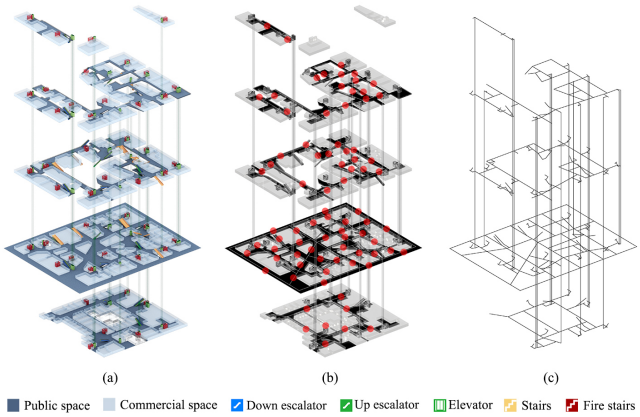


Figure 4. (a) The function of TaiKoo Li Sanlitun (b) The spaces accessed by customers and observation points (c) The segment model.

3. Analysis and result

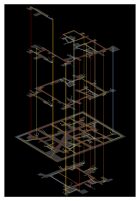
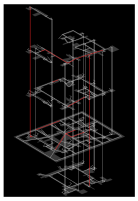
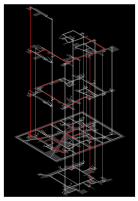
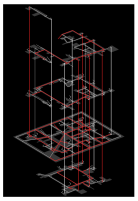
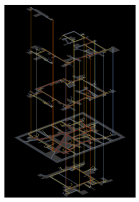
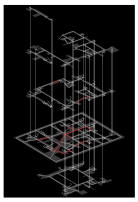
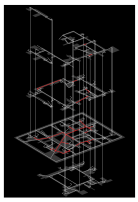
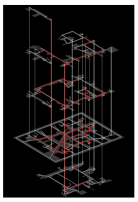
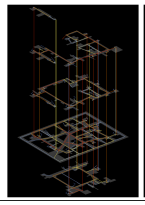
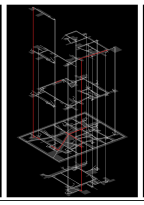
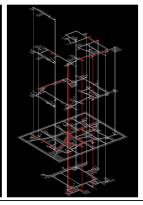
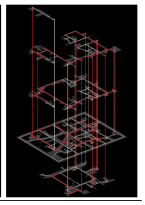
Figure 4 illustrates the distribution of Taikoo Li Sanlitun. This study's research area is the customer area of Taikoo Li Sanlitun due to the employee areas and firefighting spaces are inaccessible to customers. The all fourth floor of the building is inside the stores, so it is not included in the modeling area. After building the network, we first calculate the BC distribution for three distances: topological, metric, and angular distance. Then we calculate the pedestrian flow using the deep learning algorithm and then compute the MLR model. In the last section, we explain the phenomenon of spatial hyperlinks using the MLR model.

3.1. SPATIAL NETWORK CHARACTERISTICS

The site is rectangular, and the building above ground is divided into 19 separate volumes. Horizontally, the paths are distributed in a grid above the ground and a ring on the underground floor. Vertically, elevators, escalators, and stairs are uniformly distributed in it.

Table 2 shows the three BC distributions and we use top 5%, 10% and 25% as quantiles. The common point of the three is the vertical distribution of centrality, where the closer a floor is to the ground floor, the more paths of high BC the level contains. The distribution of metric BC varies most between floors, with its high centrality paths heavily distributed on the ground floor. And the distribution of topological BC differed least between floors.

Table 2. The distribution of betweenness centrality.

Centrality	Distribution of Centrality	Top 5% Segment	Top 10% Segment	Top 25% Segment
Topological BC				
Metric BC				
Angular BC				

3.2. MLR ANALYSIS

This study uses the MLR analysis to find out the relationship between pedestrian flows and other parameters, including parameters representing spatial hyperlinks.

We conducted three field studies on October 24, November 8, and November 15, 2020, all of which were sunny. We set 102 observation points to shot videos, and 228 videos were taken(Figure 4). Each video is about 5 minutes long. We calculate the pedestrian flow from these videos in each observation point.

Figure 5 shows the unary linear regression (ULR) model calculated by N(the pedestrian flow count) and BC. When using three types of BC, the R^2 is 0.169(topological BC), 0.349(metric BC), and 0.111(angular BC). The three R^2

are too small to a weak correlation statistically. As a result, there is a weak relationship between the N and the three BC. Using BC alone is not useful in predicting the pedestrians' distribution in Taikoo Li Sanlitun.

We used the MLR model to solve the above problem. The results show that the R^2 calculated using the three BC is 0.797(topological BC), 0.869(metric BC), and 0.745(angular BC), all of which are substantially higher than the R^2 using ULR analysis. And the three MLR models are respectively capable of explaining 79.7%, 86.9%, and 74.5% of the pedestrian distribution. The F ratio (64.53, 108.7, and 48.11, respectively) in both models is highly significant (p<0.001). Apparently, by adding other parameters into the linear regression process, the BC becomes a significant regressor.

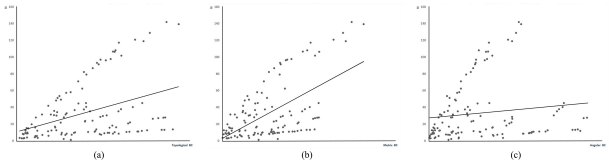


Figure 5. the unary linear regression (ULR) model.

Table 3. The result of multiple linear regression model.

	MLR(Angular BC)				MLR(Metric BC)				MLR(Topological BC)			
	coef	std err	t	P>|t|	coef	std err	t	P>|t|	coef	std err	t	P>|t|
Constant	-6.8886	6.260	-1.100	0.273	-12.5329	4.504	-2.782	0.006	-13.2235	5.706	-2.318	0.022
C	83.0336	8.986	9.240	0.000	92.9765	5.621	16.540	0.000	70.8225	6.065	11.677	0.000
H_1	-14.2049	7.175	-1.980	0.050	-12.3862	5.105	-2.426	0.017	-15.5276	6.403	-2.425	0.017
H_2	22.5801	7.855	2.875	0.005	21.8448	5.601	3.900	0.000	19.7715	6.957	2.842	0.005
B_1	24.5090	9.444	2.595	0.011	21.0589	6.757	3.117	0.002	22.2331	8.410	2.644	0.009
F_1	58.2460	6.613	8.808	0.000	48.4158	4.792	10.104	0.000	54.5597	5.916	9.222	0.000
F_2	18.1750	7.740	2.348	0.021	2.6603	5.608	0.474	0.636	7.9659	6.936	1.149	0.253
F_3	-4.7520	7.108	-0.669	0.505	-7.3102	5.107	-1.431	0.155	-6.6594	6.356	-1.048	0.297

Table 3 presents the results of the statistical significance analysis for each of the independent variables for the three MLR models using the T-test. In all three models, the coefficients F_2(p=0.253) and F_3(p=0.297) are unimportant when using topological BC, the coefficients F_2(p=0.636) and F_3(p=0.155) are unimportant when using metric BC, and the coefficients Cnatant(p=0.273) and F_3(p=0.505) are unimportant when using angular BC. And in all models, parameters H1 and H2 that characterize the spatial hyperlinking phenomenon are statistically significant.

We compare the t value of each independent variable in the three models, and it characterizes the variables' contributions. In descending order, the contributions of the topological BC model and angular BC model to the seven coefficients are C, F_1, H_2, B_1, H_1, F_2, and F_3, and the metric BC model's order is $C, F_1, H_2, B_1, H_1, F_3$, and F_2. This result indicates that BC has the most significant influence on the people's distribution in Taikoo Li Sanlitun. In the four coefficients about the floor, the ground floor(F_1) has the most enormous effect on people's flow. Among the two coefficients related to spatial hyperlinks, escalators(H_2) have a greater influence than elevators(H_1). The escalator's slope

is positive, while the elevator's slope is negative in the opposite direction in all three equations.

3.3. EXPLANATION OF SPATIAL HYPERLINK

This section compares two types of spatial hyperlinking paths, elevators and escalators from the three MLR models.

Figure 6 shows that three average BC of elevators is higher than three BC of escalators, but the count of the pedestrian flow of the escalators(*33.054 person/min*) is much greater than it of the elevators(*10.392 person/min*). As shown in 3.2, the regression coefficients for H_1 are positive, and H_2 are negative, indicating that the people's number on a path is positively correlated with the path being an escalator and negatively correlated with being an elevator. This means that the flow of people in an elevator is less than the ordinary path with equal BC(H_1<0), whereas the flow of people in an escalator is greater than the ordinary path with equal BC(H_2>0).

Figure 6. average BC of elevators and escalators .

The causes of this phenomenon are as follows. There are two reasons for the low maximum number of people that the elevator path can carry. One is the elevator itself can only take a limited number of people. For example, the elevator in Taikoo Li Sanlitun has a maximum load of 1000kg and a maximum capacity of 13 people each time, as stated in the Chinese national standard. The other is the elevators have to stop operating to pick up or set down passengers. Contrary to elevators, escalators can carry far more pedestrians, and they generally do not stop working. That is why escalators have a positive spatial hyperlinking effect, but elevators have a negative one.

4. Discussion

This study quantifies the phenomenon of spatial hyperlinks using a network science approach. However, three factors might affect the analysis.

First, this paper studies only one case, so the findings' generalizability needs to be verified. We hope to use the same approach in future research to study more commercial complexes to draw more generalized conclusions.

Second, this study focuses on the commercial complex's spatial network and does not include building perimeter paths. However, the spatial network of the building's surroundings can also have an impact on the inside spatial network, which can also influence the conclusions of this study.

Third, this research uses Yolo-v3 for pedestrian flow counting, which is not completely accurate for identification. For example, the façade of Taikoo Li Sanlitun uses many reflective materials, such as glass, mirrors and metal panels, which leads to errors in pedestrian identification due to duplicate records when recognition. It is not only necessary to avoid selecting observation points in areas with reflective materials but also need to adopt a more appropriate human recognition algorithm in the future.

5. Conclusion

This paper quantifies the phenomenon of spatial hyperlinks by using an MLR model and identifies the effects of two types of spatial hyperlinking paths, elevators and escalators. It also attempts to provide a new perspective for researchers in architecture and urbanism to understand the complex three-dimensional spatial structures in contemporary cities. And it has the following two conclusions.

First, the BC calculated by the network science algorithm cannot characterize the distribution of people in the commercial complex, and more coefficients need to be added to represent the real distribution of the people. When multiple factors were considered together, BC's effect on the population distribution is the most significant.

Second, the phenomenon of spatial hyperlinks affects the distribution of people in commercial complexes, and the two path types with spatial hyperlinks have different effects. Escalators enhance the flow of people, while elevators do the opposite. The reasons for this are related to the operating mechanisms of the two types of paths themselves. Comparing the t values of the independent variables H_1 and H_2 in three MLR models, it is found that escalators have more influence on the people's distribution than elevators.

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