Spatial difference analysis for accessibility to high level hospitals based on travel time in Shenzhen, China

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**Abstract**

In the modern metropolis, the coverage of community hospitals is getting larger and larger. But high-level hospitals treating serious and sudden illness are still kind of scarce social resources. Shenzhen is the forefront of China’s reform and opening up, its solution to the problem of medical allocation can be used as a reference for other cities. In this paper, we assume that primary, secondary and tertiary hospitals are main places for treating major diseases in Shenzhen, and analyze each sub-districts’ spatial accessibility to them based on travel time and spatial difference within the city. A kernel density two-floating catchment area method (KD2SFCA) is used to calculate how many medical resources each sub-district could share, in which the travel time from residential district to hospitals is used as an important parameter in evaluating the accessibility between suppliers and demanders. According to statistics of travel time by both driving and public transportation, the impedance function in KD2SFCA is modified and actual data of Shenzhen is used to fit its parameters, which could better simulate the attenuation trend of hospital service capabilities over the travel time. The spatial accessibility are calculated under different travel modes and multiple time thresholds, and then spatial autocorrelation analysis method is used to analyze the spatial correlation of residents’ accessibility to these medical resources. From both analysis of spatial accessibility and spatial autocorrelation, distinct variations in spatial distribution of high-level hospitals could be observed: of which the south and central parts of Shenzhen have significantly higher accessibility, while the eastern and western regions are relatively lower. In particular, 12 sub-districts gain quite lower scores than others, showing that constructions on high-level hospitals should be strengthened further. In conclusion, the spatial configuration of high level hospitals in Shenzhen is not well balanced, further optimization is urgently needed.

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1. Introduction

Public service facilities provide essential resources and services for people’s survivals and developments, such as those for education, health, culture, sports, transport, social welfare and security. The rationality on spatial distribution affects their allocation fairness and efficiency, and also the quantity and quality of public services that each individual could share and the achievement of the goal of “equalization of basic public services”. As the foundation of peoples’ health and life safety, hospitals are the most important public service facilities, their spatial allocation rationality guarantees an equal opportunity for people to enjoy necessary medical treatments.

Accessibility to basic public services represents the relative location value and convenient degree of public facilities to meet social and economic activities within a city or region, This concerns the equity and justice of urban public resources’ allocation and is
regarded as an important symbol for the quality of urban life (Michalos, 1999). In 1959, Hansen suggested that accessibility providing potential opportunities for interaction and it was a desire and ability to overcome space separation, and employment, shopping opportunities and activities of citizens were taken as basic objectives to evaluate this accessibility (Hansen, 1959); Pooler proposed such accessibility to urban public services referred to the relatively close spatial relationship between the facilities’ distribution and their users (Pooler, 1995). The most commonly used measurement includes distance method, opportunity cumulative method, contour method, probability method, frequency method, balance coefficient method, temporal method, and methods based on matrix or topological space syntax and so on (Cheng & Lu, 2007). These methods are constantly being improved and new methods are proposed, such as potential model, the two-step floating catchment area method, the kernel density method and methods based on time geography. In 1982, Joseph proposed the concept of potential model in the research of the accessibility to medical service in the Wellington County (Joseph & Bantock, 1982). Potential model reflects the spatial competing effects between facilities and demanders, which includes facilities’ competitions for the demanders and the demanders’ competitions for limited resources, the calculation formula of which is the quantitative description for the number of the public service resources that residents access. Radke and Mu proposed the two-step floating catchment area (2SFCA) method (Radke & Mu, 2000), it repeats the process of floating catchment twice (once on supply locations and once on demand locations). 2SFCA is based on potential model, incorporating the interaction among supply, potential demand, and travel cost in their characterization of spatial accessibility, which is now a key measurement of spatial accessibility, particularly in applications of primary health care access. Luo and Wang used a modified 2SFCA to carry out an empirical study of accessibility to public health care facilities, which distinguished areas with shortage facilities by setting distance or time thresholds, and effectively reflected the status of residents’ choice on facilities across administrative boundaries (Luo & Wang, 2003). These methods take the interaction between supply-side and demand-side into account, but how to determine the critical distance is their common difficulty. The often used models improved based on 2SFCA are EZ2SFCA and KD2SFCA and etc., in EZ2SFCA the catchment is broken into several discrete zones with different constant weight applied to the accessibility within each one; instead of creating discrete zones, the KD2SFCA uses a continuous decay function (Paul, 2013; Matthew, 2012).

For accessibility to medical facilities, Higgs selected the number of beds, the number of doctors, transportation supply, population density and others as evaluation factors (Higgs & Gould, 2001); Hare used the ratio of the number of beds, the number of inhabitants and different critical distances to discuss the accessibility to medical facilities for cardiovascular diseases (Hare & Barcus, 2007).

Chinese government regards rational spatial accessibility as an important principle for layout of the public service facilities (Song & Chen, 2010). But the study on spatial accessibility to health care facilities is still in initial stage in China. Y. Wang put forward a geographic accessibility calculation method by using GIS technology and the Voronoi polygon for the study of accessibility to public medical service of Pudong district of Shanghai (Wang, 2006). L. Zhang applied the accessibility with visual programming language Delphi and MapX to Yizheng’s hospital planning in Jiangsu (Zhang, Lu, & Zhao, 2008). H. Tao improved the potential model and used it to analyze the shortage area of medical facilities in Zhuhai district of Guangzhou (Tao, Chen, & Li, 2007); Z. Liu studied the spatial accessibility to medical facilities for the 8 districts of Beijing based on the 2SFCA method (Liu, Guo, & Jin, 2007).

As the forefront of China’s reform and opening up, Shenzhen is one of the fastest growing cities in China. Besides economic and social development, public health and fair treatment begins to increasingly draw more attention both in governmental and public. Some scholars studied the spatial distribution of some critical diseases in Shenzhen. Hu demonstrated substantial geographic variation in the incidence of hepatitis B infection and hepatoma in Shenzhen (Hu & Du, 2014). Y. Wang analyzed the spatial-temporal variation of IHD hospital admissions from 2003 to 2012 by spatial statistics, spatial analysis and space-time scan statistics (Wang & Du, 2014). Z. Wang applied hierarchical Bayesian models to explore the spatial heterogeneity of the relative risk for hypertension admissions throughout Shenzhen in 2011 (Wang & Du, 2014).

Meanwhile, Shenzhen has made efforts to improve medical conditions, constructing a two-level medical service system which includes community and high level hospitals to solve basic medical problems for a population more than 10 million. A reform on public hospitals is also implemented, aiming to vigorously transform general outpatient clinics in high level hospitals to special clinics, which goal is that by 2015, more than 70% of such transforming achieved and the number of outpatient firstly diagnosed in community hospitals takes more than 40% of the city’s total. By using economic instruments, Shenzhen government proposed large hospitals to shunt general outpatient clinics to community hospitals. The medical service system has gradually realized first diagnosis in community hospitals and two-way referral pattern between the two levels (Shenzhen Health Statistic, 2011). In this way, the public with minor illnesses can get basic medical treatments in community hospitals, only those with serious illnesses need to go to high level hospitals. In this case, the configuration issues of high level hospitals have become more important in the health fair of the majority public.

In view of this, the paper aims to research the spatial distribution relationship between high level hospitals and population by using KD2SFCA method, calculates the accessibility and analyzes the spatial variation of these medical institutions with spatial autocorrelation analysis method, and finally to figure out areas which is short of health services, which could provide a reference for the future plan of hospitals.

This paper is organized as follows: Section 2 briefly introduces the study area and methods and the relevant data for Shenzhen; Section 3 describes the results of the spatial distribution characteristics and trends; and Section 4 draws conclusions and discusses potential future studies.

2. Data and methods

2.1. The study area

Shenzhen is a coastal city located in south Guangdong, China, near to Hong Kong, and on the east coast of the Pearl River, with its extent of longitude 113°46′ to 114°3′, latitude 22°27′ to 22°52′. There are 10 administrative districts under the jurisdiction of Shenzhen, they are Futian, Luohu, Nanshan, Yantian, Bao’an, Longgang, Guangming, Pingshan, Longhua and Dapeng. The area of the city is 1991.64 km², in 2013 the city’s resident population is 10,547,400, of which household population is 2,876,100. Shenzhen is China’s major international gateway to communicate with other countries, it is a wonderful microcosm of China’s reform and opening-up and modernization. In 1980, under the leading of Mr. Deng Xiaoping, Shenzhen was designated to be China’s first special economic zone. A small town with 30,000 population has been developed into a metropolis with tens of millions of people after 34 years, creating a miracle in world’s history of industrialization, urbanization, modernization.
Fig. 1. The distribution of high level hospitals in Shenzhen.

Fig. 2. The distribution of doctors in high level hospitals of Shenzhen.

Fig. 3. The distribution of population for each sub-district in Shenzhen.
2.2. Data sources

2.2.1. Hospital data of Shenzhen
At the end of 2012, there were 2008 health institutions, 26124 sickbeds and 76684 health workers in Shenzhen. From view of the possession of per thousand population, there was 2.65 sickbeds, 7.27 health workers, 5.87 health technicians and 2.27 practicing doctors in average (Shenzhen health Statistic, 2012). In this paper, we study mainly on the primary, secondary and tertiary hospitals in Shenzhen, which were high level hospitals in the two level medical service system. The distribution of these hospitals is shown as Fig. 1. The three red crosses from largest to smallest represent tertiary, secondary and primary hospitals, respectively.

The number of practicing doctors for these hospitals is shown in Fig. 2. From the contrast of Figs. 1 and 2, the number of practicing doctors is basically proportional to the level of the hospitals, therefore, the higher grade the hospital is, more doctors it preserves.

In the following calculation of accessibility, we used the number of the practicing doctors of these hospitals as indicator to represent their service capability, since this is always one of the most important factors to attract patients.

2.2.2. Population data
Sub-districts are taken as the minimum spatial units for the study of the accessibility to high level medical institutions in Shenzhen. There are 58 sub-districts, including a free trade zone. The population data of these sub-districts was obtained from the census data in 2010, among which the most populous sub-district having 580736 people, while the free trade zone with only 1849 in total. The administrative center of each sub-district is treated as the center of its scope, which was obtained via Baidu Map (Baidu Map). A population distribution map is made as Fig. 3 by combining the population data with their locations. In the following calculation of accessibility, population of each sub-district is used as the indicator to represent the degree of its demand.

2.2.3. Travel time
The travel time to doctors is taken as the main factors restricting people’s accessibility to hospitals. Therefore, The travel time from residents to hospitals is the basis for accessibility calculation. This paper does not calculate the travel time by using distance and a hypothetical speed based on vector maps, but used Baidu Map API to get the travel time with help of digital maps and dynamic traffic information from data provider (Baidu Developer). The geographical data come from NavInfo, which is a leader in China providing digital maps, dynamic traffic information services and big data vertical applications based on positions. It has been consistently
Fig. 8. The accessibility for the sub-districts in both modes with increasing thresholds.
committed to offer professional and high-quality geographical information products and services to global customers. In field of dynamic traffic information service, NavInfo provides intelligent travel information such as traffic jam and accidents, transportation forecast, dynamic parking lot and flight information (Navinfo).

NavInfo not only provides varieties of data but also update them in high frequency. The travel time calculated accounting for the traffic flow and transfer time etc. is more objective than that only considering the travel distance and a hypothetical travel speed. By this method, the huge workload on road data acquisition is avoided and the results reliability is improved.

2.3. Methods

The KD2SFCA method was adopted to calculate the spatial accessibility to high level hospitals in Shenzhen at the level of sub-district. The essence of the result calculated by KD2SFCA is the supply-to-demand ratio of each demand location within the scope in a given threshold, and the calculation is divided into two steps, which mathematical models are shown in the followed formulas:

Step1 : for each hospital(j), 
\[ D_j = \frac{\sum_{k \in [d_0 \leq d_0]} P_k f(d_{kj})}{\sum_{k \in [d_0 \leq d_0]} P_k} \] (1)

Step2 : for each sub-district(i), 
\[ A_i = \sum_{j \in [d_0 \leq d_0]} D_j f(d_{ij}) \] (2)

In the first step, for each hospital location, search all sub-districts locations k that are within a threshold of travel time from hospital j and compute the supply-to-demand ratio Dk within the catchment area. In formula (1), dk,j is the travel time between sub-district k and hospital j, d0 is the threshold of travel time for the range of hospital services, Pk is the demand at sub-district k that falls within the catchment which in this paper is represented by population of the sub-districts, and Sj is the capacity of hospital j which is represented by the number of practicing doctors. f(d) is the impedance function defined in formula (3), which assumes that even within the same catchment, people would give preference to the closer hospital than other father ones, and the longer the travel time, the less possibility of the hospital to be selected. The most popular impedance functions are Gaussian, Inverse power and Exponential (Kwan, 1998). Here the Gaussian is chosen, since with a slow rate of declination, it won’t fall sharply to zero. Here is the Gaussian function as formula (3):

\[ f(d) = \begin{cases} e^{-d^2/k}, & d \leq d_0 \\ 0, & d > d_0 \end{cases} \] (3)

Next, for each sub-district location i, search all hospital locations j within the threshold of travel time (d0) and sum up the supply-to-demand ratio Dk at those hospital locations to obtain the accessibility Ai at sub-district location i. In this step, the attenuation of the supply is also considered, so the impedance function f(d) is applied in formula (2). Ai with higher value indicates a better accessibility (Wang, F. 2006), while lower ones meaning areas of shortage. The two steps of KD2SFCA can be written as formula (4):

\[ A_i = \frac{\sum_{j \in [d_0 \leq d_0]} S_j f(d_{ij})}{\sum_{k \in [d_0 \leq d_0]} P_k f(d_{kj})} \] (4)

3. Results and discussion

Residents’ preference to hospitals is influenced by various factors, such as geographical location, service quality, price, medical condition and the environment. The calculation model of spatial accessibility used in this paper takes the number of practicing doctors as an indicator to characterize the capabilities of the hospital's service and considers the travel time's influence on people's choice for hospitals.

3.1. Travel time and its impedance function

The proximity of services relative to the location of the population is one of the important characters of access (McGrail, 2012). Travel time is a critical feature for spatial relationship between origins and destinations, which well demonstrates the proximity between such pairs. Further considering that time is of great importance in curing diseases, especially for those sudden and serious diseases, this paper uses travel time to calculate the spatial accessibility.

In view of peoples travel habits, the time taken from residents and hospitals is calculated in both driving and public transport. Since there are 58 sub-districts and 108 high level hospitals, there could be 5264 shortest routes in total. The statistics for the travel time are shown in Figs. 4 and 5.

The statistics reflect that the average time by driving from the residents to hospitals is 38 min, with a minimum of 1 min and a maximum of 111. By contrary, the average time by public transport is 102 min, which having a 12 min minimum and a 330 maximum. The time for routes without bus arrivals is excluded in the calculation. It is clear to find that time consumed by public transport is about 2.68 times than the driving mode.

As mentioned in 2.3, this paper assumes that even within the service scope of the hospital, an increasing travel time would reduce its attraction, and in return it would reduce the supply capacity of the hospital service. That’s why an impedance function like formula (3) is introduced to describe such attenuation.

In order to determine the parameters of this function, it is assumed that all residents could find the right hospital for doctors before reaching the maximum travel time, in other words, the potential of hospitals is close to zero for far-away patients with maximum travel time. Therefore, a further assumption is that when the maximum travel time by driving and public transport are 110 and 330 min respectively, the constant k could be derived as 4050 and 33650 when the impedance function having a value of 0.05.

In cases with minimum travel time, the service capacity of the

<table>
<thead>
<tr>
<th>Threshold time</th>
<th>Moran’s I</th>
<th>Z-Value</th>
<th>P-Value</th>
<th>Threshold time</th>
<th>Moran’s I</th>
<th>Z-Value</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>9.5 min</td>
<td>0.1143</td>
<td>1.6060</td>
<td>0.068</td>
<td>25.5 min</td>
<td>-0.0142</td>
<td>0.2359</td>
<td>0.329</td>
</tr>
<tr>
<td>19 min</td>
<td>0.5060</td>
<td>5.9166</td>
<td>0.001</td>
<td>51 min</td>
<td>0.4849</td>
<td>5.1759</td>
<td>0.001</td>
</tr>
<tr>
<td>38 min</td>
<td>0.5140</td>
<td>6.0756</td>
<td>0.001</td>
<td>102 min</td>
<td>0.5228</td>
<td>6.0718</td>
<td>0.001</td>
</tr>
<tr>
<td>57 min</td>
<td>0.5432</td>
<td>6.6433</td>
<td>0.001</td>
<td>163 min</td>
<td>0.5622</td>
<td>6.7667</td>
<td>0.001</td>
</tr>
<tr>
<td>76 min</td>
<td>0.4728</td>
<td>6.0492</td>
<td>0.001</td>
<td>204 min</td>
<td>0.5004</td>
<td>5.8951</td>
<td>0.001</td>
</tr>
</tbody>
</table>
Fig. 9. LISA Cluster Map for the accessibility to hospitals.
hospital would be fully supplied, that is to say, the value of the impedance function should be 1 in such situations. In order to achieve this, formula (3) is modified by an added parameter of $d_{min}$ as formula (5) shows.

$$f(d) = \begin{cases} \frac{e^{-(d-d_{min})^2/k}}{d_{min}} & d \leq d_{min} \\ 0 & d > d_{min} \end{cases} \quad (5)$$

In formula (5), when the travel time equals $d_{min}$, the value of the function would be 1. For driving and public transportation modes, the $d_{min}$ parameter is set to 1 and 12 min respectively. And results are shown in Figs. 6 and 7.

In the driving mode of Fig. 6, the attenuation of the service capacity is less than 30% when the travel time equals to the average. While in mode of public transport shown in Fig. 7, the attenuation approximates to 20% under an averaged travel time.

3.2. Results for accessibility

According to the travel time distribution, a mean value is used as the basic reference, then thresholds of 0.25, 0.5, 1, 1.5 and 2 times of such mean time are made as the threshold of the travel time for the patients to choose hospitals. Therefore, thresholds for travel time by driving is 9.5, 19, 38, 57 and 76 min, and there are 25.5, 51, 102, 163 and 204 min for public transport.

Fig. 8 shows the accessibilities of the 58 sub-districts to hospitals in both driving and public transport modes, the value means the number of doctors per thousand people possess. The left column is computed by driving time, and ones in right are computed by public transport time. In this group of figures, the natural breaks (jenks) method is used to classify the accessibilities into five grades with each class given a different color. The deeper the color, the better the accessibility to hospitals is, vise versa. The spatial distribution of the accessibility can be seen roughly from these figures. In the micro level, within the same mode of transportation, the accessibilities have significant difference with different thresholds such as (a1) and (a2); while between different modes, the accessibilities have slightly difference with almost equal distances like (a3) and (b3). However, in the macroscopic level, both sides reflect the same regularity that areas with high accessibility aggregated in the south and central parts of Shenzhen while the threshold of the travel time increasing.

3.3. Spatial autocorrelation analysis for accessibilities

In order to identify the spatial distribution regularities and regions in lack of high level hospitals, the spatial autocorrelation analysis for accessibilities is applied based on the above calculations. We use Queen Contiguity weight method to calculate Global Moran's I, and generated Local Indicators of Spatial Association (LISA) Cluster Map. Through the autocorrelation analysis of accessibility in different threshold, each Global Moran's I value and its Monte Carlo Test is obtained as the following Table 1.

As can be seen from the Table 1, For each test, Moran’s I is larger than 0, Z-value is higher than 1.96 except when the threshold time is 9.5 min for driving and 25.5 min for public transport. So these
two sets of values have low significance, while all other 8 results for spatial autocorrelation are significant at 99.9% confidence level.

It is shown that sub-districts’ accessibilities to hospitals calculated either based on drive or public transport have certain positive spatial correlations except for the threshold of 9.5 min in driving mode and 25.5 min for public transport. The Moran’s I value calculated by accessibility under these two thresholds have a lower value, indicating that in such situations the correlations of each sub-districts’ accessibility are relatively weak. The reason for this result may be that with the shortest threshold people can only visit hospitals within a small local area which making the hospitals unachievable by people outside this region and eventually lead to obvious regional differences. However, by other ‘normal’ thresholds of 19, 38, 57 min (driving) and 51, 102, 163 min (public transport), the accessibilities to hospitals show an increasingly strong positive correlation. When with thresholds of 76 min and 204 min for driving and public transport respectively, this correlation begins to decrease though it is still positive. It is estimated that with the increasing time threshold, residents of sub-districts could get more medical resources, and thus reduce the spatial variation of the accessibilities to hospitals. From results of different travel modes, it can be seen that there are similar spatial distributions and trends for both aggregation areas with high and low values in the spatial autocorrelation analysis with the time by driving and public transport.

LISA Cluster Map obtained from spatial autocorrelation analysis is shown in Fig. 9. Ones on the left side are computed with the accessibility value by driving time, while the right are by public transport time. Red areas represent regions with high aggregation (legend titled by High—High) and the blue for low aggregation (legend titled by Low—Low).

Results on the analysis of the 10 LISA Cluster Maps are lists in Table 2. Sub-districts’ appearance in the High—High and Low—Low areas is counted as frequency, and used to find most and least developed medical regions in Shenzhen.

According to Table 2, for areas of high value and low value aggregation, the frequency inclination of each sub-district is presented in Figs. 10 and 11 separately.

Figs. 10 and 11 tell that the high and low aggregation areas generated from the spatial autocorrelation experiments are roughly the same. 19 sub-districts including Guiyuan, Dongmen, Cuizhu, Sungang, Huaqiangbei, Yuanling, Nanyuan, Shatoujiao, Futian, Nanhu, Meilin, Dongxiao, Huafu, Lianhua, Huangbei, Buji, Xiangmihu, Qingshuikou and Minzhi have high frequency in the High—High aggregation area, which means these sub-districts have high accessibility to the high level hospitals. Shiyuan, Daling, Guanlan, Xixiang, Guangming, Kuiyong, Dapeng, Gongming, Shajing, Nanbao, Songgang and Longgang have high frequency in Low—Low aggregation area, meaning they are the areas lacking of such resources. These frequency statistics can be shown as Fig. 12, where the red areas have a high accessibility, and the blue areas have a low accessibility. It can be concluded that those sub-districts with blue color belong to shortage area for high level hospitals and the government should further make efforts to build more and better hospitals.

4. Conclusions

This study aims to understand the spatial layout and distribution of the high level medical resources at the sub-district level in Shenzhen by using KD2SFCA and spatial autocorrelation analysis method. Considering the importance of time in curing diseases, especially in the sudden or serious one, the travel time instead of the spatial distance from residential districts to high level hospitals is used in the calculation of spatial accessibility. In view of that peoples with different habits or income may use different modes of transportation, both the time by driving and public transportation are computed by using the API provided by Baidu Map. These travel times are analyzed and their mean value is taken as a reference, which 0.25, 0.5, 1, 1.5 and 2 times are used as thresholds in the KD2FSCA method.

Results of the 10 analysis on accessibilities using travel time both by driving and public transport present similar spatial distribution for sub-districts in Shenzhen. The quantitative spatial autocorrelation analysis further proves that there are obvious areas with high value clustering and low value clustering. While sub-districts of Guiyuan, Dongmen, Cuizhu, Sungang, Huaqiangbei, Yuanling, Nanyuan, Shatoujiao, Futian, Nanhu, Meilin, Dongxiao, Sungang, Huaqiangbei, Yuanling, Nanyuan, Shatoujiao, Futian, Nanhu, Meilin, Dongxiao,
Huafei, Lianhua, Huangbei, Buji, Xiangmihu, Qingshuihe and Minzhi have a high value clustering. Shiyan, Dalang, Guanan, Xixiang, Guangming, Kuyi, Keping, Denglong, Shajing, Nanao, Songgang and Longgang present relatively lower values meaning that they are lack of high level medical resources. In view of spatial distribution, the medical resources of the central and southern regions are extremely in abundance. However, northwest and southeast regions which are in scarce deserve enhancement by government. These results can be used by urban public health officials and related decision makers to allocate public health resources and formulate medical-related policies. Unfortunately, the method in this paper does not take account residents’ income, preferences and other factors which leaves improvement for further research.

Conflicts of interest

The authors declare no conflict of interest.

Acknowledgments

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