**Exploring Effects of Network Structure on False Alarm of Planar K-Function**

**Abstract**: Network spatial analysis is a hot research topic in the field of spatial analysis. The results of network spatial analysis are clearly related to the study object and the network that the object lies in. K-function is a method generally used for evaluating the distribution pattern of spatial point sets. Applying the planar K-function to analyze the network spatial phenomena may lead to false alarm problems, i.e. inconsistency between planar and network K-functions. Therefore, what kind of network would produce a false alarm is the focus of this article. The same underlying question is that how the network structure affects the network K-function. The present article explored the above questions by changing the network structure while keeping the analyzed point set fixed. The results demonstrate that the network structure has an uncertain effect on false alarm, and it is difficult to determine what kind of network will create a false alarm problem. The results in this paper are inconsistent with those of existing studies. These findings suggest that the strategy of using empirical methods to find the rule of network spatial analysis failed.

**Key words:** Network spatial phenomena; Planar K-function; Network K-function; False alarm

**1 Introduction**

Network spatial analysis is a hot and important research topic in the spatial analysis field. The study object is phenomena or events that are adjacent to, alongside or occurring on a network, the so-called network spatial phenomena【这句法错了吧】. Geometrically, they can be abstractly expressed as points or point groups. Since the calculation and analysis depend on the network in which the point groups are located, clearly the results of the network spatial analysis are related to that network.

Extending the classical analysis methods of Euclidean space to network space is one of the main approaches to network spatial analysis, such as network kernel density estimation and network K-function. The network K-function method is used for spatial point pattern analysis along networks. Over the past decade, the network K-function method has been widely applied to analyses in areas like medical care, urban crime, traffic accidents, ecology and economy.

The planar K-function may over-detect clustering patterns, and may underestimate the clustering of point groups too. The incorrect predictions【estimation？】 of the distribution pattern of point groups by planar K-function are called false alarms, which include false positive (FP) problems and false negative (FN) problems. As defined by Lu and Chen, a FN problem of the planar K-function refers to the scenario when the planar K-function analysis indicates a non-clustering or a relatively weak clustering pattern while the network K-function analysis shows a clustering or a strong clustering pattern. Similarly, when the planar K-function analysis shows a clustering pattern but the network K-function analysis designates a non-clustering or a relatively weak clustering pattern, a FP problem occurs. Instead, if the patterns detected by planar and network K-functions are consistent, no false alarm problem exists and this situation can be called neutral.

Yamada and Thill analyzed the clustering of vehicle accidents along highways in Buffalo, New York, and concluded that the planar K-function tends to over-detect the clustering because the Euclidean distance is not appropriate for measuring the distance between traffic accidents. Lu and Chen indicated that in a poorly connected street system, the Euclidean distance is shorter than the actual street distance for the extra turns and long travel distances between places. They analyzed the patterns of vehicle thefts in San Antonio and reached a preliminary conclusion. On the network with high street length density and segment density, false negative is expected to be a problem. And the planar K-analysis tends to result in a false positive conclusion on the network with low street length density and segment density. It is obvious that the high street length density and segment density links to high accessibility of the network, and contrarily, the low density indicates low accessibility. Garrocho-Rangel et al studied the intraurban agglomeration of economic units with planar and network K-functions. The empirical analysis of the central business district (CBD) in Toluca indicates that the network K-function is more appropriate for detecting the agglomeration in high-density networks, which is consistent with the findings of Lu and Chen. This means that given the high density in CBD road networks, the planar K-function underestimates the clustering, while the network K-function detects the pattern more clearly. The number of business also has an impact in generating the required simulations to determine confidence levels. Lamb et al analyzed four different scenarios including motorcycle road accidents and random network constrained events in Tampa, and fast food restaurants and pharmacies in New York. The network K-function results were compared in three network structures (integrated, original, and directed). It was found that the topologically correct networks (integrated network structure) lead to more clustering, for the distance between events in the topologically correct network is shorter in a better-connected network.

It can be seen from the above studies that the factors affecting the network K-function results mainly include: network structure, the number of point groups and their distribution characteristics on the network. For the same point group, the planar K-function result is fixed. However, when the point group is distributed in different networks, the network K-function results differently. As shown in Fig. 1a, the planar K-function of a certain point group shows clustering, when the same point group is distributed in different networks, the network K-functions demonstrate a clustering and a repelling phenomenon respectively. Therefore, there is no false alarm phenomenon【problem】 in Fig. 1b, but a false positive problem in Fig. 1c. The planar K-function of the same point group does not change with the changes of the network structure in which the point group is located, nevertheless, the network K-function varies with the changes of the network. Therefore, how the network structure affects the false alarm and how it affects the results of network K-function are in nature the same question.

**Figure 1. Distribution of the same point group in different spatial contexts and its K-functions. (a) A point group and its planar K-function; (b) (c) Distribution of the same point group in two network spaces and their network K-functions.**

There are different understandings of network structure. In Lu and Chen’s study, the network structure is measured by street density and segment density. In the study by Lamb et al, it is referred to the topology of the network. In the analysis and identification of road network mode, it refers to the morphological structure formed by roads on the network, such as grid pattern, radiation pattern, and ring pattern. In the present study the network structure refers to the number of roads and how the roads are connected on the network.

Changes in the network structure would cause changes 【in】 the road density and the way the roads are connected on the network. Then, as the network structure changes, what happens to the false alarm? For example, would it change from FP to neutral or would it change from FN to FP? In this study, the control variates method is adopted, keeping the point group fixed while changing the network, to explore how the network structure affects the false alarm. The same question we tried to answer is what effects the network structural change has on the network K-function.

The rest of the paper is organized as follows. Section 2 introduces the concepts of the planar and Network K-function and the definition of network and road network. Section 3 explains the basic ideas and experimental design of this study. Section 4 presents the data. Section 5 gives the experimental results and analysis. Section 6 concludes the paper.

**2 Basic Concepts**

**2.1 Planar K-function and Network K-function**

Ripley’s K-function, also known as the planar K-function, is a point pattern analysis method based on second-order analysis. It evaluates the dispersion characteristics of points in a global scale and does not need experiential parameters. It is much better than other point pattern analysis methods like the nearest neighbor distance method and the kernel density estimation. The method needs considerable computing and time costs, limiting its use to only hundreds of points. New approaches were proposed later to accelerate the calculation process.

For a single point in a point set, Ripley’s K-function is the comparison of the observed intensity of the point with the expected number of points within a certain distance, defined as:

 (1)

where E(d) is the expected number of points within the range of distance d, and λ is the intensity of the points. For a whole point set, Ripley’s K-function is defined as:

(2)

where A is the area of the points region and n is the number of points. When the distance dij between point i and j is less than a given range d, then Iij(d)=1. Otherwise Iij(d)=0. wij is the weight function that makes up for the segment effect because of the conflict between the circle of dij and the region boundary.

For a point set that is completely spatially random (CSR),  is expected to be . For points that are clustered, it is expected that  and for points that are regularly distributed, . In order to test the significance of whether the distribution is CSR or not,  can be transformed in to  as:

** (3)

Therefore, when a point set is clustered, , and when a point set is regular within distance d, . Otherwise when a point set is randomly distributed, .

The Monte Carlo simulation method is usually used in hypothesis tests. The method generates many realizations that are randomly distributed and compares the observed point set with all those realizations to test the significance of observations on CSR. Confidence interval is set to determine whether the observation can be seen as clustered, dispersed or randomly distributed.

The network K-function method, proposed by Okabe and Yamada, analyzes the distribution of spatial points along networks, extending the measure of distance from Euclidean to the shortest path. The network K-function is computed along a finite network, which is somewhat different from the computation in a planar space.

In a network composed of links and nodes, the distance between two points is measured by the length D of the shortest path between them. Points are assumed to be distributed independently and randomly on the whole network, which is reflected in the probability density function below:

(4)

where LT is the network, |LT| is the length of the total network and f(p) is the probability of a point p distributed on LT. For a subset LS of LT, the probability of point p can be given by a binomial distribution, which is known as binomial point process, according to Ripley (1981). Then the network K-function for point p can be defined as:

(5)

where ρ is the density of the points, E(·) is the expected value and NP is the number of points within network distance D of a point p on . The observed network K-function is then defined as:

(6)

where n is the total number of the points. The network K-function is meant to compare the observed values with expected values, which follow the binomial distribution. When , the point pattern along networks is considered to be clustering, and if , the point pattern is considered to be repelling.

**2.2 Definition of a road network**

**Definition 1:** The road networks can be divided into planar road networks and nonplanar road networks. A road network that can be embedded in a plane is called a planar road network, otherwise it is a nonplanar road network.

For example, in the road of Fig. 2a, a person can select any road at the cross of the roads. Such a planar road network in the analysis model is shown in Fig. 2b that the four edges are crossed and connected to each other at one node, and any one edge is only crossed at that node. In contrast, in the urban road network there exists a grade-separated intersection where one road passes over another, just as the interchange of the highway and the normal road in Fig. 2c. Such a non-planar road network in the analysis model is shown in Fig. 2d that there exist edges that are crossed but not connected. The present study focus on the planar road network.

**Figure 2. Road intersection and interchange and the corresponding networks. (a) (b) Planar; (c) (d) Non-planar.**

Fig. 3 shows a simple road network. The network K-functions of the non-planarized and planarized road network were calculates and the results are shown in Fig. 3b and c. Evidently, the network K-function results are significantly different. The present study only considers the planar road network. Therefore, the road network data needs planarization before the calculation of the network K-function, that is, the road network data is broken so that only the vertex of each edge intersects with each other.

**Figure 3. A point group and its network K-functions with different sets of linear units on the same road network. (a) Distribution of a point group on the network; (b) Network K-function after planarization; (c) Network K-function before planarization.**

**Definition 2:** The planar road network (RN) consists of node set V and link set L, where the link set L corresponds to the set of road segments in the real world, and the node set V represents the set of segment endpoints in the real world. Since the segments on a planar network only intersect at the endpoints, the node set V contains the intersections of all segments.

**Definition 3:** The phenomena or events at specific locations on a planar RN (e.g. fast-food restaurant, the places where car accidents occur) can be abstracted as event points. The set of a certain type of event points can be noted as P={p1, …, pm}, where m is the number of event points. Different from the nodes in the RN, these event points can be located anywhere in the link set L including the endpoints.

When analyzing the event points on a planar RN, we need to combine the node set V and the event point set P into a point set VP=V∪P. The edge set L of the RN is further segmented by the point set VP to obtain a new planar analysis network AN=(VP, S) which is spatially coincident with the RN.

**Definition 4:** The edge set S of the analysis network AN is the set of segments containing all linear units after segmentation. A linear unit that connects two points in the VP without passing through a third point is called a segment.

**Definition 5:** The segments in the analysis network AN can be divided into two categories. The segments on the shortest path between any pair of event points are called key segments, and the others are called ordinary segments, as shown in Fig. 4.

The key segment affects whether the event points are directly connected, whereas the ordinary segment does not.

**Figure 4. Concepts in network point event analysis.**

**3 Methodology**

**3.1 Basic ideas**

This study employs the control variates method, that is, keeps the event point set unchanged while changes the network structure to study the impact of the network structure on the false alarm phenomena. The network structure of this study refers to the number of roads and how the roads are connected.

From the network K-function equation (6), it can be seen that for the same event point set, given a fixed total length of the network (i.e. the same density), if the event point set is in a network that can have more points directly connected, then more event points will fall into the h neighborhood of some event point, resulting in a larger observed value of the network K-function corresponding to the distance h. Therefore, one of the practical factors affecting the network K-function is the connectivity of event points, but not the connectivity of the entire network.

For the same event point set (Fig. 5a), two networks with the same density but different connectivity of event points can be constructed (Fig. 5bc). The network shown in Fig. 4c directly connects more event points, resulting in better connectivity and a larger observed value of the network K-function (Fig. 5d).

**Figure 5. Effects of connectivity of event points on network K-function. (a) An event point set; (b) A network with poor connectivity of event points; (c) A network with good connectivity of event points; (d) Observed values of network K-functions.**

Furthermore, the principle of the network K-function indicates it as a relative concept that compares the observed value of K-function of the event point set to the K-function value of a random point set on the same network. On the same network, if the connectivity of event points is superior to that of the random points, the network K-function demonstrates clustering; whereas if the connectivity of event points is inferior to that of the random points, the network K-function indicates repelling.

Another factor affecting the network K-function is road density, as high-density road networks are more likely to provide high connectivity of event points. However, this is not an exclusive situation, as high-density road networks may also increase the connectivity of random points.

From the above analysis we can see that if keeping the event point set fixed, the primary factors affecting the result of network K-function analysis are the connectivity of event points on the network (how the roads are connected) and the road density. In this study it is intended to change these two factors by adjusting the network structure, calculate the network K-functions of the same event point set on different network structures, and summarize the changes of the network K-function and its effects on the planar K-function false alarm phenomena. Hence, how to change the network structure is the key issue of this study.

**3.2 Network structural change**

**3.2.1 Operators of network structural changes**

A network change cannot be arbitrary. It requires determinism and operability. Taking into account the changes in connectivity of the event points (no change, increase, and decrease) and the changes in road density (no change, increase, and decrease), there are a total of nine combinations. The operators to make these changes are summarized in Table 1. The operators are organized at the conceptual level.

**Table 1. Operators of network structural changes**

Among these operators that change the road structure, some are not in line with the actual situations, or the randomness of the operation is too large to be controlled. For operator 1, the added key segments cannot fit in the actual roads. For operators 2, 3, 4, 5, and 7, the changed roads have large uncertainties, and the directions and distances of the added segments are difficult to determine. Eventually, there are three operators that can be realized: operator 6, 8, and 9 (highlighted in gray in table n). (1) The key segments are deleted, the connectivity of event points is decreased, and the road density is decreased as well; (2) The key segments are broken, the connectivity of event points is decreased, and the road density remains the same; (3) The ordinary segments are deleted, the connectivity of event points keeps unchanged, and the road density is decreased.

3.2.2 Algorithm for network structural change

The algorithm is the actual operation of an operator. According to the practicable operators that change the network as discussed, the corresponding algorithms are designed. A key issue in the algorithms for network structural change is how to measure the relative importance of a segment to determine the order of segment deletion and breaking. Characteristic path length is commonly used as a parameter to measure the overall connectivity of network nodes. Here in this study, we chose to use the change of characteristic path length to measure the impact of a segment on the connectivity of points on a network, since it can reflect the change of network distance of all point pairs by deletion of a network segment. The larger change in the characteristic path length after deletion of a segment, the more important the segment is; otherwise, the less important the segment is. The equation for calculating the characteristic path length is as follows:

(7)

where n is the number of event points, and is the shortest path length between event point i and j. Then the importance of each segment can be calculated with:

(8)

where is the importance of the ith segment, is the characteristic path length of event points after the ith segment is removed, and is the characteristic path length of event points of the original road network.

Deleting or breaking key segments can be conducted in either ascending or descending order by importance. Since the ordinary segments have no effects on the connectivity of event points, they have no value of importance here. Eventually all the ordinary segments will be deleted. Hence, the ordinary segments are deleted in ascending order of segment lengths, and the same results will be achieved in other orders too. The algorithms corresponding to these three operators are listed in Table 2.

**Table 2. Algorithms for network structural change**

|  |  |  |  |
| --- | --- | --- | --- |
| Operator | Control variates | | Algorithm |
| Connectivity of event points | Density |
| Deleting key Segments | Decrease | Decrease | Step1: Find the set S of all segments on the shortest paths between all pairs of event points.  Step2: Calculate the importance of each segment in S.  Step3:   1. Ascending strategy: According to the ascending order of importance of the segments in S 【依次遍历每一条边】, check whether the deletion of a segment will cause network disconnection or event point isolation. If not, the segment will be deleted, otherwise the segment will be retained ~~until all segments in S are checked~~. 2. Descending strategy: According to the descending order of importance of the segments in S, check whether the deletion of a segment will cause network disconnection or event point isolation. If not, the segment will be deleted, otherwise the segment will be retained ~~until all segments in S are checked~~.   Step4: Repeat Step1-3 until no segment available for deletion. End of operation. |
| Breaking key Segments | Decrease | No change | Step1: Find the set S of all segments on the shortest paths between all pairs of event points.  Step2: Calculate the importance of each segment in S.  Step3:   1. Ascending strategy: According to the ascending order of importance of the segments in S【依次遍历每一条边】, check whether the breaking of a segment will cause network disconnection or event point isolation. If not, the segment will be broken, otherwise the segment will be retained ~~until all segments in S are checked~~. 2. Descending strategy: According to the descending order of importance of the segments in S【依次遍历每一条边】, check whether the breaking of a segment will cause network disconnection or event point isolation. If not, the segment will be broken, otherwise the segment will be retained ~~until all segments in S are checked~~.   Step4: Repeat Step1-3 until no segment available for breaking. End of operation. |
| Deleting ordinary segments | No change | Decrease | Step1: Find the set S of all segments that are not on the shortest paths between all pairs of event points.  Step2: Delete segments in ascending order of segment lengths until S is an empty set. |

**3.3 Experimental design**

The experiment in this study consists of three steps:

Step 1: Prepare the event point sets with a false negative problem, a false positive problem, and no false alarm problem (Neutral), respectively. The details are shown in Section 4.

Step 2: For each event point set in Step 1, change the network structure according to Section 3.2 (including deleting the key segments in respective ascending and descending orders of importance, breaking the key segments in respective ascending and descending orders of importance; and deleting the ordinary segments), calculate the network K-functions after the network change, and summarize the changes of the network K-functions. The details are shown in Section 5.1.

Step 3: Analyze the changes in the false alarm phenomenon and compare them with previous studies. The details are shown in Section 5.2.

**4. Data**

The experimental data is part road network and three groups of points of interest (POIs) in Bao’an District, Shenzhen, China, including:

(1) 185 commercial companies, randomly distributed according to the planar K-function but clustered according to the network K-function, serve as a false negative instance of the planar K-function analysis, as shown in Fig. 5a.

(2) 183 medical facilities, clustered according to the planar K-function but randomly distributed according to the network K-function, serve as a false positive instance of the planar K-function analysis, as shown in Fig. 5b.

(3) 187 educational facilities, clustered according to both the planar and the network K-functions, serve as a no false alarm (neutral) instance of the planar K-function analysis, as shown in Fig. 5c.

**5 Results and Discussion**

**5.1 Changes in the network K-functions**

According to Step 2 in Section 3.3, the road network structures were changed according to the five strategies regarding the three operators respectively, and the corresponding network K-functions were calculated.

The results of deleting the key segments in ascending order of importance are shown in Table n. The decrease of (dashed line) is larger than that of (solid line), and the final network K-function results all demonstrated clustering.

**Table n. Results of deleting key segments in ascending order of importance**

The possible reason for the above results might be that the deletion of the key segments in ascending order of importance reduces the connectivity of event points and the road density, but reduces the connectivity of random points even more. To confirm it, we used SANET to generate the same amount of random points\*, and calculated the characteristic path lengths of random points and real points, respectively, as shown in Table 3. The characteristic path lengths of random points are exclusively larger than the lengths of real event points, which meant that on a new network, the connectivity of random points is less than the connectivity of event points. For the three different datasets, the network K-functions all exhibited clustering phenomena.

**Table 3. Characteristic path length of random points and real points**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dataset | Characteristic path length of random points on original network | Characteristic path length of real points on original network | Characteristic path length of random points on processed network | Characteristic path length of real points on processed network |
| False Negative Data | 3263.944 m | 3098.189 m | 7866.045 m | 6510.276 m |
| False Positive Data | 3263.944 m | 3152.424 m | 6682.825 m | 5413.741 m |
| Neutral Data | 3263.944 m | 2713.395 m | 7232.725 m | 5136.404 m |

The results of deleting the key segments in descending order of importance are shown in Table n. The decrease of (dashed line) is smaller than that of (solid line), and the final network K-functions demonstrated a random, repelling and repelling phenomenon, respectively.

**Table n. Results of deleting key segments in descending order of importance**

**Figure 8. Results of deleting key segments in descending order of importance. (a) False negative problem data; (b) False positive problem data; (c) Neutral data. For each row, the left part is the original road network, the middle part is the road network after deleting the key segments, and the right part is the network K-function before and after the deletion.**

The road networks and network K-functions of breaking the key segments in ascending order of importance are shown in Fig. 9. As shown, the decrease of (dashed line) is larger than that of (solid line), and the final network K-function results were all clustering.

**Figure 9. Results of breaking key segments in ascending order of importance. (a) Network K-functions before and after breaking the key segments of the false negative problem data; (b) Network K-functions before and after breaking the key segments of the false positive problem data; (c) Network K-functions before and after breaking the key segments of the neutral data.**

The results of breaking the key segments in descending order of importance are shown in Fig. 10, showing that The decrease of (dashed line) is smaller than that of (solid line), and the network K-functions exhibited a random, repelling and repelling phenomenon, respectively.

**Figure 10. Results of breaking key segments in descending order of importance. (a) Network K-functions before and after breaking the key segments of the false negative problem data; (b) Network K-functions before and after breaking the key segments of the false positive problem data; (c) Network K-functions before and after breaking the key segments of the neutral data.**

The values of network K-functions do not change after deleting the ordinary segments, whereas the values are increased. The network K-functions demonstrated random ，repelling, random in some areas and repelling in other parts (Table n).

**Table n. Results of deleting ordinary segments**

The above results are summarized according to the changes in network structural parameters and shown in Table 4. It can be seen that the network structural changes may change the observed values of the network K-functions and the envelope of stimulated maximum and minimum values, or only change the envelope of stimulated maximum and minimum values, with various degrees of influence, thus affect the relative values of them, and further change the point distribution patterns indicated by the network K-function.

**Table 4. Network K-functions before and after network structural changes**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Network structure | Strategy | K-function | Connectivity of event points | Road density | False negative data | False positive data | Neutral data |
| Original |  | Planar K |  |  | Random | Clustering | Clustering |
|  | Network K |  |  | Clustering | Random | Clustering |
| After deleting key segments | Ascending | Network K | **↓** | **↓** | Clustering | Clustering | Clustering |
| Descending | Network K | **↓** | **↓** | Random | Repelling | Repelling |
| After breaking key segments | Ascending | Network K | **↓** | **=** | Clustering | Clustering | Clustering |
| Descending | Network K | **↓** | **=** | Random | Repelling | Repelling |
| After deleting ordinary segments |  | Network K | **=** | **↓** | Random | Repelling | Random and clustering |

**(“=” represents no change, “↓”represents decrease, “clustering”, “repelling” and “random” represent the point pattern corresponding to K-function)**

For instance, the third row of the table indicates that after the key segments are deleted in ascending order of importance, the connectivity of event points is decreased, the road density is decreased, and the result of the network K-function of the false negative data is clustering, that of the false positive data is clustering, and that of the neutral data is clustering. Row 4-n could be explained similarly.

**5.2 Comparison**

Previous studies reach two main inferences regarding the false alarm of planar K-function: (1) In the circumstances of good connectivity of event points and high road density, false negative problems tend to occur; (2) In the circumstances of poor connectivity of event points and low road density, false positive problems tend to occur.

**Table 5. Relationship between the results of tested false alarm problems and the previous inferences.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Network Structure | Strategy | False Negative Data | | False Positive Data | | Neutral Data | |
| After deleting key segments | Ascending | False Negative | × | Neutral | × | Neutral | **-** |
| Descending | Neutral | **-** | False Positive | √ | False Positive | √ |
| After breaking key segments | Ascending | False Negative | × | Neutral | × | Neutral | **-** |
| Descending | Neutral | **-** | False Positive | √ | False Positive | √ |
| After deleting ordinary segments | | Neutral | **-** | False Positive | √ | False Positive | √ |

**(“**×**” represents inconsistent with previous inferences; “**√**”represents consistent with previous inferences; “-” represents not mentioned in previous studies)**

The results of individual experiments were discussed first. Taking the deletion of key segments in ascending order of importance as example, for the data with a false negative problem, it is still false negative after deleting the key segments, indicating that the false negative problem still occurs in the circumstances of poor connectivity of event points and low road density. For the data with a false positive problem, after the key segments are deleted, the connectivity of event points is decreased, and the road density is decreased too, but as a result, the false positive phenomenon disappears and the false alarm changes to neutral. This is completely different from the previous inference. Our results demonstrated that a false positive problem may still occur in the circumstances of good connectivity of event points and high road density, but a false positive problem may not occur necessarily in the circumstances of poor connectivity and low road density.

Regarding breaking key segments in ascending order of importance, for the data with a false negative problem, it is still false negative after breaking the key segments, indicating that a false negative problem may still exist with poor connectivity of event points. For the data with a false positive problem, after the key segments are broken, the connectivity of event points is decreased, but the false positive phenomenon disappears and the false alarm changes to neutral. This is also completely different from the previous inference. The results showed that a false positive problem may still exist with good connectivity of event points, but a false positive problem may not occur necessarily with poor connectivity.

With respect to the overall experiment results, compared to the original data, the processed data has either lower road density, either lower connectivity of event points, or both. According to the previous inference (2), a false positive problem is more likely to happen in the processed data. The frequency of false alarm problems in the processed data is calculated (Table 6). It is found that for the original false negative data, in the corresponding processed data the frequency of the false positive problems is smaller than that of the false negative problems and the neutral results, clearly inconsistent with the inference (2).

With respect to the false alarm results of the processed data, the frequency of false alarm problems in original data is shown in Table 7. Compared with the processed data, the original data has either larger road density, either better connectivity of event points, or both. However, from row 2 of Table 7, it can be seen that the number of false negative problems is lower than that of false positive problems and neutral results. Similarly, in the third row of Table 7, both false negative and false positive problems show up. This is evidently contradictory to the inference (1).

**Table 6. Frequency of false alarm problems in processed data.**

|  |  |  |  |
| --- | --- | --- | --- |
| False alarm situations in original data | Frequency of false alarm problems in processed data | | |
| False negative | False positive | Neutral |
| False negative data | 2 | 0 | 3 |
| False positive data | 0 | 3 | 2 |
| Neutral data | 0 | 3 | 2 |

(For instance, the first row indicates that in the processed data corresponding to the original false negative data, there are two groups of data with false negative problems and three groups with neutral results).

**Table 7. Frequency of false alarm problems in original data corresponding to processed data.**

|  |  |  |  |
| --- | --- | --- | --- |
| False alarm results of processed data | Frequency of false alarm problems in original data | | |
| False negative | False positive | Neutral |
| False negative | 2 | 0 | 0 |
| False positive | 0 | 3 | 3 |
| Neutral | 3 | 2 | 2 |

(For instance, the third row indicates that for those processed data with neural results, in the original data three groups have false negative problems, two groups have false positive problems, and two groups have neutral results)

**6. Conclusion**

The present study explored the impact of network structure on false alarm problem and network K-function by changing the network structure. The results showed that it is difficult to determine what kind of network would produce a false alarm problem, or we can say that the impact of the network structure on the network K-function is unknown. The present results are in contradiction with the existing studies. According to the results of this study, it is found that the strategy of finding the rule of network spatial analysis by specific empirical studies did not actually work. Then, the focus of our next step is whether we can find some network model, just like randomly generating points on the network, that always produces FN or FP on the network model (the network K-function results are always clustering or random), and conduct deductive research based on that model.

For the clustering analysis of points, edge effects play a very important role. In this paper, no modification to handle edge effect is applied to any of the K-function analyses for the computational difficulty in correcting the edge effect for the network K-function, same with the previous studies.