Key Location Discovery of Underground Personnel Trajectory Based on Edge Computing

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Abstract. With the rapid development of smart mines, workers' trajectories can be accurately tracked and generate massive positioning data. However, how to quickly find useful information in a large amount of data is an important issue at present. Consequently, in this paper, we propose an algorithm for application in underground edge computing systems, called key location discovery (KLD). First, the algorithm reconstructs the trajectory data by the potential semantic information of the underground environment and miners work types to be more suitable for the actual situation. Then, the KLD algorithm screen out the key locations of underground personnel trajectories according to inflection point and stay point. In the meanwhile, compared with the trajectory structure-based hot spots (TS_HS) discovery algorithm, KLD algorithm reduced the positioning data by 1/4 and calculating time. In addition, placing the algorithm proposed in this paper on the edge side for calculation and processing can filter out key information in real time, which is more beneficial to the follow-up work, including the study of personnel trajectory abnormalities and prediction.

Keywords: Personnel trajectories analysis · Inflection point · Stay point · Edge computing

1 Introduction

With the rapid development of the mining economy, people have higher and higher requirements for the safety of underground traffic and the speed of data

Supported by the National Key Research and Development Program of China (2017YFC 0804402).

J. Liu et al. (Eds.): MobiCASE 2020, LNICST 341, pp. 134–142, 2020.
https://doi.org/10.1007/978-3-030-64214-3_9

processing. Currently, various positioning equipments such as radio frequency identification, ZigBee [2], WiFi [6], Bluetooth [5], and UWB [3] have been placed in the coal mines and its surrounding areas. Therefore, an increasing quantity of positioning data can be gathered and transmitted by positioning stations underground to the ground server. However, the method of transferring data to the server takes a lot of time, causing delay in information processing, so that the movement and safety status of underground personnel cannot be observed in real time.

Therefore, combining the advantages of edge computing, this paper proposes an algorithm for data processing on the edge side, that is, key location discovery, which can quickly filter out useful information and find key positions. First, considering the semantic information of underground workers, the paper classifies the trajectories of the same type of work according to the miners' job information, which is more suitable for the actual situation. Then, the KLD algorithm reconstructs the trajectory data, and it can screen out the key locations of underground personnel trajectories according to inflection point and stay point. Compared with other algorithms, The KLD algorithm reduced the positioning data by 1/4, thereby removing redundant data.

2 Materials and Methods

A key position underground is a point with special semantics in the trajectory, such as crossroads and work areas. These positions are points with high trajectory density. However, a high-density point is not necessarily a key position point. The trajectory of the wellhead is relatively dense, but the wellhead does not have much practical significance for the overall trajectory of the moving object. Therefore, the emphasis of this chapter is to filter the key positions sequences in the massive trajectory data, that is, a sequence of positions or regions with special semantics in the trajectory. For actual situations in the well, the KLD algorithm flowchart is shown in Fig. 1. First, because different types of work have different activity areas and characteristics, the paper divides the discrete positioning points into different personnel trajectories with semantic information according to the type of work information, which is convenient for subsequent work. Then, different types of trajectory points are used to determine whether it is an inflection point according to the turning angle. If the result is positive, it is added to the key sequence. Otherwise, it continues to be used to judge whether it is a stay point until all the trajectory points are traversed. The important semantic points in the trajectory are extracted to form a key position sequence, thereby reducing data redundancy and calculation complexity.

2.1 Personnel Semantics

Because of the different divisions of labour, the underground workers' trajectories have their own characteristics. Table 1 shows part of the positioning data log. The trajectory data consist of a series of orbital positioning points, including

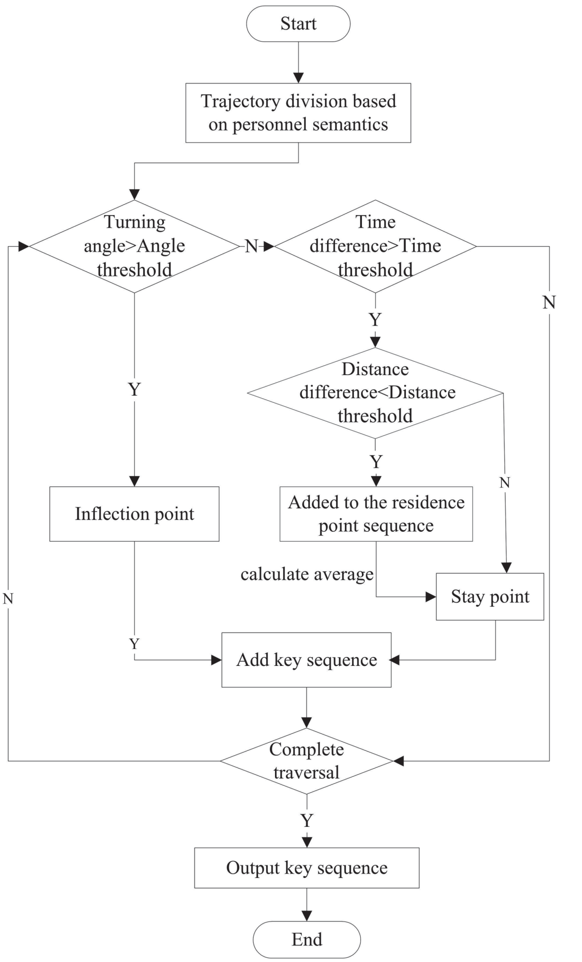

Fig. 1. KLD algorithm flowchart.

Table 1. Positioning data log

Number	Type of work	Name	Initial reporting time	Last reporting time	Location number
1	Group I comprehensive Coal Mining Team	Mr. Chen	2017-12-20 06:05:42	2017-10-2 06:06:27	96
2	Group I comprehensive Coal mining team	Mr. Chen	2017-12-20 06:07:04	2017-12-20 06:07:31	3103

the type of work, the name of the miner, the initial reporting time, and the last reporting time. The latitude and longitude of the miner can be determined according to the location number.

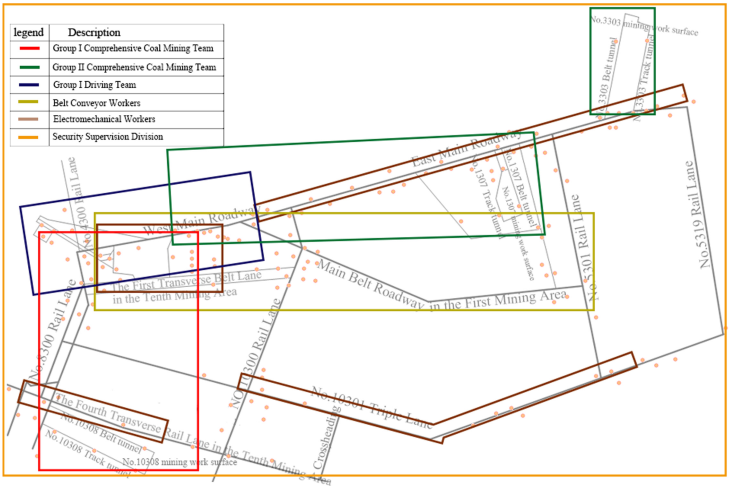

Fig. 2. Semantic schematic of some coal miners

As shown in Fig. 2, a coal mining area displays the semantic information of six kinds of coal miners. The main function of the security supervision division is to monitor the production safety in the mine, so the miners' trajectories are all over the coal mine. The main function of the belt conveyor workers is to control the belt conveyor, which determines that their working area is fixed, and their moving path is limited. The driving team is the roadway excavation team, so there are more stopping points in their trajectories than in other trajectories. The function of the comprehensive coal mining team is to mine coal in a specific working surface, so their trajectories will stay in the working surface area for a long time. Considering the semantic information of underground workers, it is necessary to classify the trajectories of the same type of work according to the miners' job information before trajectory processing so that the trajectory information mining is the most accurate and most suitable for the actual situation.

2.2 Detection of Inflection Point

The inflection point is the turning angle of the adjacent trajectory segments, which can reflect a trend in the moving object trajectory [1]. The working area in the mine is relatively fixed, and most of the roads are linearly distributed. When the moving object in the mine has turning or wandering behaviour in the working area, an inflection point of the corresponding angle is generated, so the inflection point in the trajectory can be regarded as an important position point. In Fig. 3, α is angle at the inflection point from trajectory P_3P_4 to trajectory P_5P_6, that is, the inflection point is the point P_4. It can be seen in the figure that the formula to calculate the angle is as shown in Formula 1.

$$\angle\alpha = \arccos\left(\frac{P_3P_4^2 + P_4P_5^2 - P_3P_5^2}{2 \times P_3P_4 \times P_4P_5}\right) \tag{1}$$

where

$$P_3P_4 = \sqrt{(x_3 - x_4)^2 + (y_3 - y_4)^2}$$

$$P_4P_5 = \sqrt{(x_4 - x_5)^2 + (y_4 - y_5)^2}$$

$$P_3P_5 = \sqrt{(x_3 - x_5)^2 + (y_3 - y_5)^2}$$

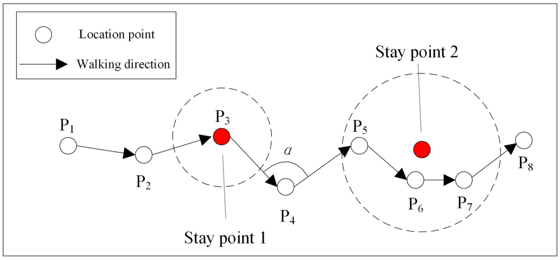

Fig. 3. Stop point diagram

Algorithm 1. Inflection Point Detection Algorithm

Input: Trajectory datasets.
Output: Inflection point set and non-inflection point set.
1: **for** every trajectory **do**
2:    **for** every point **do**
3:       calculate the turning angle α;
4:       **if** $\alpha >$ threshold **then**
5:          the point is inflection point;
6:       **else**
7:          the point is noise point or stay point;
8:       **end if**
9:    **end for**
10: **end for**

The screening formula for the inflection point is shown in Formula 2, where β is the angle threshold. When the inflection point of point P_i is less than or equal to β, it indicates that the moving object has changed its original trajectory at this point, so the point is marked as an important position point. When the angle is greater than β, it means that the moving object has a tendency to maintain its original motion trajectory, so it is necessary to further study the point to determine whether the point is a noise point or a stay point. Through many experiments, a better effect can be obtained by setting β to 110°.

The time complexity for calculating the inflection point is *O(n)*, where n represents the number of location points. The Algorithm 1 is a pseudo code for inflection point detection.

$$P_i = \begin{cases} \text{an important position point}, & \alpha \leq \beta \\ a \text{ noise point or a stay point}, & \alpha > \beta \end{cases} \tag{2}$$

2.3 Detection of a Stay Point

A stay point is a geographical point where the moving object stays for a long time. It may be a work area or a rest area in the mine. Stay points can be divided into two cases. The first is that the moving object stays in the same position within a certain time range. As shown in Fig. 3, the time that the moving object stays at point P_3 exceeds the time threshold, so P_3 is a stay point. The second case is that in a certain time range, the moving object wanders in a specific space [4]. As illustrated in Fig. 3, the moving object moves at P_5, P_6 and P_7 for greater than the time threshold, but the moving distance is less than the distance threshold. Therefore, the stay point 2 calculated by the average value of points P_5, P_6 and P_7 indicates the staying behaviour.

Algorithm 2. Stay Point Detection Algorithm

Input: Non-inflection point datasets.
Output: Candidate key sequence set.

```
for every point do
    calculate the time difference between adjacent points;
    if time difference > time threshold then
        calculate the distance difference between adjacent points;
        if distance difference < distance threshold then
            calculate the average value to add to the key sequence;
        end if
        add to the key sequence;
    end if
end for
```

The stay point detection method in Algorithm 2 is based on the heuristic judgement of the distance threshold and the time threshold. First, it is determined whether the time difference between point P_1 and point P_2 is greater than the time threshold. If the condition is satisfied, it is determined whether the distance between the two points is less than the distance threshold. If the distance is less than the distance threshold, the requested stay point is the first case, and point P_2 is added to the key region sequence. Otherwise, it indicates that the requested stay point is the second case, and the two points P_1 and P_2 are added to the residence point sequence. The above process is repeated to determine whether the location point should be added to the residence point sequence until the distance threshold or time threshold is not satisfied. The average of the latitude and longitude of the location points in the residence point sequence is used to indicate the position of the stay point. The selected stay points are added to the key region sequence, and the other points are marked as noise points. Through several experiments, this paper set the distance threshold 50 m and the time threshold to 20 min.

3 Results and Analysis

The experimental data includes three months of underground personnel data, including the group I comprehensive mining team, the group II comprehensive mining team, the group I mechanized excavation team, and the group I tunneling team, with a total of 126,687 track points.

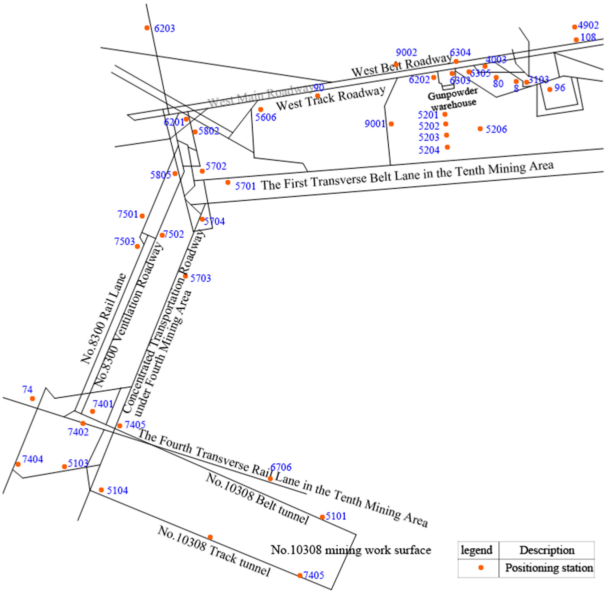

Fig. 4. Activity map of the group I comprehensive coal mining area

Figure 4 shows the specific activity map of the group I comprehensive coal mining team surrounded by the red frame in Fig. 2. The orange dots in the figure indicate the positioning stations. Each positioning station has its own number to indicate the position information of the moving object.

Using the above positioning data to conduct experiments, because the TS_HS algorithm does not process the data set, the effect of using the KLD method and not using the KLD method on the size of the data set is compared. Comparing the size of the original dataset with the size of the dataset after processing by the KLD method is shown in Fig. 5.

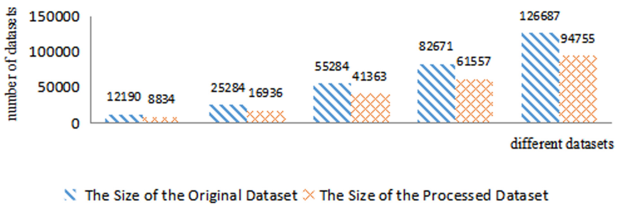

Fig. 5. Comparison of the quantity of raw data with the quantity of data processed by KLD

It can be clearly seen from Fig. 5 that experiments are performed on different data sets, and it is verified that the data sets processed using the KLD algorithm is reduced by approximately 1/4 of the track points compared to the original data sets. The reason is that we filter out the trajectory points that satisfy the inflection points and the stop points, and delete meaningless and non-semantic points, thereby reconstructing the original trajectory, and reducing data redundancy and computational complexity. In addition, in the subsequent cluster analysis work, DBSCAN is a data-sensitive analysis method, so the reduction of data quantity can greatly improve the analysis speed of DBSCAN algorithm.

4 Conclusions

For massive positioning information, it is particularly important to be able to quickly and effectively mine effective information, especially algorithms that are sensitive to data volume. Therefore, this paper proposes to perform key position screening on the edge side, namely KLD algorithm. The algorithm uses inflection points and the stay points for trajectory reconstruction and simplifies approximately 1/4 of the anchor points. It can reduce calculating time and convert the positioning data into a sequence of key positions with specific semantics.

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