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Research Article

Research on Precision Marketing Model of Tourism Industry Based on User's Mobile Behavior Trajectory

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With the deep cross-border integration of tourism and big data, the personalized demand of tourist groups is increasingly strong. Precision marketing has become a new marketing mode that the tourism industry needs to pay close attention to and explore. Based on the advantages of big data platform and location-based service, starting from the precise marketing demand of tourism, we design data flow mining technology framework for user's mobile behavior trajectory based on location services in mobile e-commerce environment to get user track data that incorporates location information, consumption information, and social information. Data mining clustering technology is used to analyze the characteristics of users' mobile behavior trajectories, and the precise recommendation system of tourism is constructed to provide support for tourism decision making. It can target the tourist group for precise marketing and make tourists travel smarter.

1. Introduction

1.1. Research Background. Location-based service (LBS) is a kind of value-added service provided by the combination of mobile communication network and satellite positioning system. It obtains the location information of mobile terminal such as latitude and longitude coordinate data through a set of positioning technology and provides it to the communication system, mobile users, and related users to realize various location-related services in military and transportation. As a new mobile computing service in recent years, 80% of the world's information has time and location tags, and location services have developed to the big data stage [1]. Developing location services requires two capabilities: the ability to provide location and the ability to understand location.

The precise marketing information pushed by LBS location service can effectively tap the potential consumer demand and make a scientific and reasonable network marketing strategy based on this, which can further improve the ability of e-commerce enterprises to tap the target customers and potential customers. According to the 2017 China Mobile e-commerce Industry Research Report, the transaction scale of China's e-commerce market reached 20.2 trillion yuan in 2016, an increase of 23.6% compared with the same period of the same period of the year. China's e-commerce market is developing steadily. Among them, the online shopping has a good momentum of development, up from 23.3% in 2015. Huge market potential tempts all walks of life. In 2016, online shopping and B2B e-commerce of small and medium-sized enterprises and enterprises above scale still dominate the Chinese e-commerce market, while online tourism and local life service O2O emerge as bamboo shoots, accounting for 3% and 1.6% of the market, respectively. From 2015 to 2016, the proportion of online tourism market in China's tourism market has greatly increased, the process of product informatization has accelerated, the penetration rate has further improved, the mobile online tourism market has developed rapidly, and consumer understanding and demand and experience of tourism are changing imperceptibly and pursuing higher quality of tourism. With the further development of "Internet+" information technology, the tourism industry has huge room for development, and online travel penetration will also gradually increase.

According to the Statistical Bulletin on National Economic and Social Development of 2016 issued by the State Statistical Bureau, in the whole year of 2016, the number of domestic tourists' trips reached 4.4 billion, an increase of 11.2% over the previous year, and the income of domestic tourism increased by 15.2% to 39390 billion yuan. The number of inbound tourists reached 138.44 million, an increase of 3.5%, and international tourism revenue increased by 5.6% to $120 billion. The number of domestic residents in China has reached 135 million 130 thousand, an increase of 5.7% [2]. With the continuous promotion of the strategic pace of building a well-off society in an all-round way, tourism has become an important part of the people's daily life in China, marking that China's tourism industry has entered the era of mass tourism.

Based on this background, in the mobile e-commerce environment, based on LBS location service, research and analysis of user's mobile behavior trajectory can extract valuable user's mobile behavior features from a large number of mixed dynamic data and integrate the mobile behavior and consumer behavior of tourism users. Based on LBS location, services will integrate the mobile behavior and consumer behavior of tourism users, then excavate the marketing value of consumers, and timely achieve the marketing objectives of enterprises on the appropriate media, so that mobile e-commerce marketing becomes more accurate and effective. Through the research of this subject, the interests of enterprises, consumers, and media can be maximized at the same time, providing personalized products and services for mobile e-commerce, improving consumer loyalty and core competitiveness of mobile e-commerce and bringing higher profits for e-commerce enterprises [3].

1.2. Presentation of Problems. The data of mobile terminal users' historical consumption behavior and location movement process are recorded and stored according to the time series, forming the user's mobile behavior trajectory data, which can be collected by multiple device terminals. The user's mobile behavior trajectory data contain a lot of useful information. Mobile behavior trajectory can express the behavior activities of mobile users in the real world. These activities imply user's interests, hobbies, experiences, and behavior patterns [4]. For example, a user's activities in a week may start from home to work every day, and a user may go to shopping malls, parks, and other places on weekends. Therefore, how to effectively utilize the user's mobile behavior trajectory and extract useful information from the user's mobile behavior trajectory data is very important for the realization of personalized recommendation service.

From the view of consulting a large number of documents, there are more papers on location services than on mobile marketing. However, most of the previous articles on location services focused on the application of natural science, such as surveying and mapping technology, network development, geographic information, and so on. In recent years, the number of cross-research articles on management science, medicine, and agriculture combined with location-based services has begun to increase, most of which are the combination of location-based services and related industries to study the application or technology development of specific industries. For example, the combination of location services and logistics technology can track the journey of packages. Combining location services with electronic maps can provide catering, entertainment, discounts, and other information within a certain range according to the location of users. Combining location service with utility technology can quickly find information such as tap water, gas explosion, and so on. The main keywords of literature research include location service technology, location service system, location service terminal, location service strategy, mobile location service, and so on. Based on location, the services industry is currently considered one of the most dynamic industries. With the rapid development of mobile Internet and Internet of Things technology, more debris time has been transferred to mobile phones, tablets, and smart products [5].

The characteristics of mobile marketing, such as precision, interaction, novelty, and effective delivery, are more and more concerned and recognized by various industries. This paper focuses on the main characteristics of the end-users of the tourism industry, such as frequent location movement, strong sense of sharing, and rich demand for services. First of all, the users of online travel must be mobile users who usually do not stay in a location for a long time, and a high probability of frequent location changes will produce a large number of location data. Moreover, in general, traveling users arrive at an unknown location or move in a series of unfamiliar geographical environments, which makes travel users' demand for location-based services take precedence over personal privacy protection and enable them to obtain real-time user location information. These location data provide favorable conditions for our research. Secondly, the behavior of tourist users is quite different from that of ordinary people. In beautiful scenery and not very familiar environment, users will spontaneously produce self-awareness. Most people share location, photos, and moods through social platforms and micromessaging, and travel companies can access these social data to accurately portray users and provide accurate services for them. Third, travel users need high-quality services to obtain high-quality tourism experience. Scenic spots, accommodation, restaurants, transportation, and finance, including tour guides and their fellow travelers, are also important factors in achieving a high-quality tourism experience. These rich demands for services will generate enormous commercial value [6]. Therefore, this article adopts top-down overall analysis to design ideas from bottom to top. By analyzing the user's characteristics through the trajectory of user's mobile behavior, this paper constructs a travel recommendation system in the mobile point-to-point environment and a precise marketing model in the tourism industry based on the trajectory of user's mobile behavior, so as to provide appropriate services for the appropriate users at the right time and place, in order to provide reference for relevant tourism enterprises to achieve precise marketing.

2. User's Mobile Behavior Trajectory

2.1. User's Mobile Behavior Trajectory Definition. User's mobile behavior trajectory is based on the path that users find frequently in the location mobile path generated by daily life. The location information generated by user's daily behavior is acquired by GPS equipment sampling at a certain time interval, and the spatial position of moving object is represented by Euclidean space coordinates, discrete display in electronic map. Through moving sequence pattern mining, we can find the correlation among these discrete location information points and obtain the user's moving behavior trajectory. This will provide effective support for precision marketing in mobile e-commerce [7]. In this paper, we make the following definitions for user's mobile behavior trajectory.

Definition 1. Location information point: the position information points generated by the user's movement can be obtained by receiving devices such as GPS of mobile terminals. Each position information point indicates a position that the user has arrived at. Suppose an independent location information point is represented as two tuple $P = (Z, T)$, among them Z is the position coordinate, and its structure contains longitude $Z.\ x$ and latitude $Z.\ y$; T is the time information of arrival position Z.

Definition 2. Mobile behavior trajectory: mobile behavior trajectory can be obtained by GPS log. A mobile behavior trajectory consists of a sequence of position information points arranged in order of time attribute T. Suppose L is user's mobile behavior trajectory, then $L = P_1 \longrightarrow P_2 \longrightarrow \cdots \longrightarrow P_n$, where $P_i\,(0 < i \le n)$ denotes any sampled position information point. Mobile behavior trajectory L satisfies any $0 < i \le n$, $P_i \cdot T < P_{i+1} \cdot Ta$; n represents the number of location information points and represents it as the length n of mobile behavior trajectory.

Definition 3. Mobile behavior subtrajectory: represents the inclusion or inclusion relationship between two moving behavior trajectories. Suppose that L_1 and L_2 have two trajectories of moving behavior, where $L_1 = a_1 \longrightarrow a_2 \longrightarrow \cdots \longrightarrow a_i, L_2 = b_1 \longrightarrow b_2 \longrightarrow \cdots \longrightarrow b_n$, If there exists a positive integer $m_1, m_2, \ldots, m_i$, satisfying $1 \le m_1 < m_2 < \cdots < m_i \le n$, making $a_1 = b_{m1}, a_2 = b_{m2}, \ldots, a_i = b_{mi}$, then L_1 is said to be the moving behavior subtrajectory of L_2, or L_2 is said to be a moving behavior supertrajectory of L_1. It can be written as $L_1 \subseteq L_2$ or $L_2 \supseteq L_1$. The location information points are adjacent to the mobile behavior subtrajectory and are allowed to be nonadjacent in the original mobile behavior trajectory.

Definition 4. Support degree: the collection of all location information points of moving behavior trajectories constitute a database of mobile behavior trajectories. $\mathrm{DB} = \{L_1, L_2, L_3, \ldots, L_n\}$, where $L_i\,(0 < i \le n)$ is mobile behavior trajectory and |DB| is the number of mobile behavior trajectories in the database. The number of mobile behavior trajectory t contained in DB is t of the support in DB:

$$\mathrm{support}(L_i) = \left|\{L \mid L \in D, L_i \subseteq L\}\right|. \tag{1}$$

Definition 5. Frequent Trajectories: when the support degree of the mobile behavior trajectory is greater than or equal to the minimum support threshold, the mobile behavior trajectory is called the frequent trajectory. $\mathrm{FT} = \{l \mid \mathrm{support}(l) \ge \min, l \subseteq L, L \in D\}$, L represents the mobile behavior trajectory sequence and D represents the mobile behavior trajectory sequence set.

The user's mobile trajectory records the user's activity status in the real world, which can reflect the user's behavior preferences and potential intentions to some extent. For example, if a user moves a lot every day, he may be an outdoor sports enthusiast. Through more fine-grained analysis, we can identify users' occupations, taste habits, and so on from their frequent locations and restaurants. Therefore, mining hot spots and planning roads through multiuser mobile trajectory data sharing is an important research content of this paper.

2.2. Classification of User's Mobile Behavior Trajectory. User's mobile behavior trajectory data refer to the sequence of changes in geographic location information caused by user's own motion behavior in a certain time and space environment. These geographic location information points which change with time series can form a user's mobile behavior trajectory data according to the order of occurrence time [8]. According to the different sampling methods, we can classify these user's mobile behavior trajectory data into three categories.

2.2.1. Location Sampling-Based User's Mobile Behavior Trajectory. A trajectory formed by a change in position during the movement of a user can be sampled sequentially according to the change in position. It focuses on the information of location change when the user moves. The data obtained by this method have abundant semantic information and very detailed location change information. We can record the trajectory data of user's mobile behavior based on position sampling by recording discrete variables. The trajectory of user's mobile behavior can be represented by the sequence of sampling points with the change of moving object's position, and it can be formally expressed as

$$L = \{(x_1, y_1, t_1, \ldots), \ldots, (x_i, y_i, t_i, \ldots), \ldots, (x_n, y_n, t_n, \ldots)\}. \tag{2}$$

The location $(x_i, y_i), 1 \le i \le n$ denotes the geographical location of the mobile user at the time of t_i, and the location (x_i, y_i) of the mobile user at the time of t_i and the location (x_{i+1}, y_{i+1}) of the time of t_{i+1} are not the same.

Trajectory can be divided into three segments according to the information of stopping point, boarding point, and alighting position, and the trajectory can be preserved according to different semantics and application segments. For example, in the prediction of travel time, it is necessary

to delete the stopping point, which may be the vehicle parking or waiting for passengers, in order to measure the trajectory travel time more accurately. For some tasks that analyze the similarity between two users, it is often necessary to use the residence trajectory to reflect the user's region of interest.

2.2.2. Time Sampling-Based User's Mobile Behavior Trajectory. The change of mobile user's behavior is sampled by definite time interval to form the trajectory data of user's mobile behavior, which is called the trajectory of user's mobile behavior sampled according to time. This kind of sampling focused on the change of location information points caused by the change of mobile user's behavior at the same time interval, which has the characteristics of large data volume and wide range. The time-sampled trajectory data of user's mobile behavior is formalized as follows:

$$L = \{(x_1, y_1, t_1, \ldots), \ldots, (x_i, y_i, t_i, \ldots), \ldots, (x_n, y_n, t_n, \ldots)\},$$
$$t_i = t_1 + (i-1)\Delta t, \tag{3}$$

where L is a trajectory data of mobile behavior, Δt is equal interval time, (x_i, y_i), and $1 \le i \le n$ denotes the location of the mobile user at any time of t_i. If the time interval between the two sampling points is larger than the threshold value, the trajectory can be divided into two segments through the two sampling points.

2.2.3. User's Mobile Behavior Trajectory Triggered by Events. The trajectory of mobile user's mobile behavior, which is recorded by the system after the sensor event is triggered, is obtained by the event triggering [9]. This sampling method focuses on the event set that triggers the sensor to work. It has the characteristics of short update period and representative sampling objects. Although the behavior of mobile users changes with time, the system does not record the trajectory according to time or position, but only records the trajectory information of mobile users when they produce some specific behavior and trigger sensor events. We can also use discrete variables to record the behavior trajectory of mobile users and formalize it as follows:

$$L = \{(x_1, y_1, t_1, \ldots), \ldots, (x_i, y_i, t_i, \ldots), \ldots, (x_n, y_n, t_n, \ldots)\}. \tag{4}$$

The location (x_i, y_i), $1 \le i \le n$, denotes the location of the mobile user at the time of t_i, and the location of the mobile user at the time of t_i, (x_i, y_i) and t_{i+1} can be the same (x_{i+1}, y_{i+1}).

When the trajectory direction changes beyond the threshold value, we can mark the key points according to the direction changes and divide the trajectory into two segments.

2.3. User's Mobile Behavior Pattern Decision. According to the trajectory data of user's movement behavior, the speed of completing the trajectory is calculated by time, and then the user's behavior pattern is determined. Many problems still need to be considered, such as road congestion, construction, and even traffic accidents, which will affect the speed of user behavior. Vehicles travel much faster than people's walking speed on normal roads, but in congested or abnormal roads, the speed difference between vehicles and people's walking speed is not obvious. Therefore, the identification accuracy of trajectory velocity can only be less than 50% through time calculation [10]. In addition, the user may change several different behavior patterns in the same trip, which makes the same user's moving behavior track contain a variety of different speeds. In the overall calculation, if the average speed is obtained, it is obviously not correct to determine the user's behavior patterns. Therefore, it is necessary to divide the user's moving behavior trajectory into several trajectory segments reasonably. By comparing different trajectory segments, we can analyze whether the user has changed the behavior pattern and further improve the recognition accuracy.

How to realize the reasonable division of user movement behavior segments is the problem we want to study. As shown in Figure 1, the walking user and the driving user travel the same way, but the trajectory data of the user's movement behavior are obviously different. We can analyze the following three aspects:

(1) Because the trajectory data of user's moving behavior produced by walking often produce direction change or reciprocating motion, we can divide the trajectory segments according to the change of the trajectory data direction of user's moving behavior. In mobile scenes, people get off a bus, walk to another station to continue to take the bus process, and must pass through a section of walking, although the walking section is short, but still can show obvious direction changes.

(2) The trajectory data of mobile behavior produced by driving users do not change significantly in direction. This kind of characteristic is not affected by traffic conditions. We can train a classification model by the supervised learning method. For example, drivers do not change their direction as freely and frequently as pedestrians do, resulting in a straight line in the trajectory of the user's movement behavior, and the direction of change is not obvious [11].

(3) We can also judge user behavior patterns by the shape of user behavior trajectory data, especially the trajectory of user behavior generated by different user behavior patterns in a journey, which will have obvious morphological changes of trajectory.

3. Analysis of User's Mobile Behavior Trajectory Data

This paper studies the trajectory of user's mobile behavior generated by online travel users during their mobile process. It contains a lot of information to express the personalized behavior of mobile users. We can use data mining methods such as classification, clustering, frequent itemsets, cycle discovery, and anomaly detection to mine and analyze the trajectory of tourism users' mobile behavior.

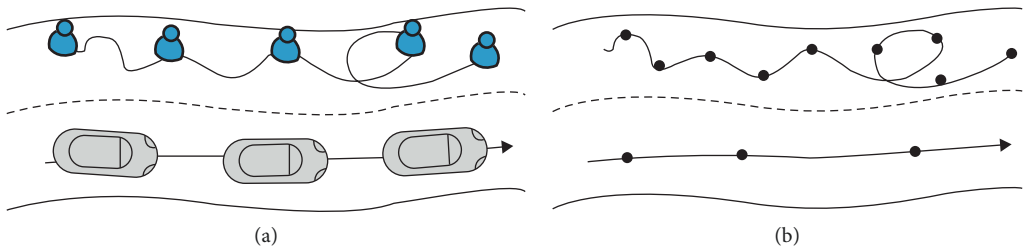

Figure 1: Differences in movement behavior between (a) walking users and (b) driving users.

3.1. Dividing Trajectory Segments. Each user movement behavior trajectory can be regarded as an image data. Structural Similarity Index (SSIM) can effectively measure the similarity of two trajectories, and clustering based on the similarity index is more accurate than traditional clustering based on Euclidean distance index [12]. The accuracy of structure similarity matching is closely related to the reasonableness and validity of the segmentation of user motion trajectory. Therefore, this section mainly studies how to detect the large-angle mutation points in the user's moving behavior trajectory, and how to partition and store the user's moving behavior trajectory records at the mutation points, so as to obtain some trajectory fragments which tend to be stable before clustering.

Each user movement behavior trajectory cannot be a straight line. As the precision of position coordinate recording is higher and higher, the direction of each track will change more and more, especially some subtle direction changes, and the angle of rotation can reflect the degree of change of the track direction. The division of track segments is determined according to the size of the track angle. However, if every corner is stored, it is not conducive to reduce the storage of the corner, and it is not conducive to extract it to divide the trajectory segments. Therefore, by storing the large turning point, we can discover and identify the changes of user behavior or abnormal conditions, which is also conducive to retaining the relatively stable local structure features of user trajectory segments.

We define the turning angle of user's moving behavior trajectory as the turning angle caused by the change of direction of adjacent trajectory segments, which can reflect the movement trend of trajectory and the change of user's behavior [13]. As shown in Figure 2, the angle between the direction changes of the user's moving behavior trajectory can be expressed as α, and the angle of rotation can be divided into outer angle and inner angle, expressed as θ_1 and θ_2, respectively. We set the outer rotation angle θ_1 as a positive value and the inner rotation angle θ_2 as a negative value to facilitate the similarity calculation of the trajectory segments.

As can be seen from Figure 2, the formula for calculating the angle alpha of the direction change is shown in Formula (5), where a, b, and c represent the adjacent and opposite sides of the angle α, respectively.

$$a = \arccos \frac{a^2 + b^2 - c^2}{2ab}. \tag{5}$$

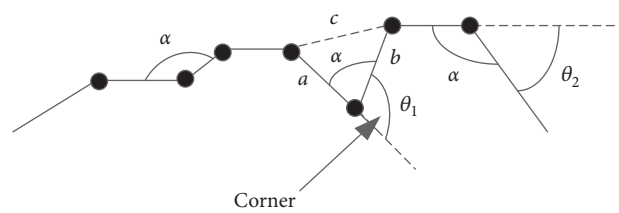

Figure 2: Corner of user's mobile behavior trajectory.

According to the above formula, the formula for calculating the angle theta can be obtained (6):

$$\theta = \begin{cases} 180 - \alpha, & \text{if } (a \times b \geq 0), \\ \alpha - 180, & \text{if } (a \times b < 0). \end{cases} \tag{6}$$

This is the first step to partition the trajectory segments of user's mobile behavior. Using formulas (5) and (6), the trajectory segment partitioning algorithm can be implemented (Algorithm 1).

Some trajectory fragments obtained by calculating rotation angle, setting threshold, and partitioning trajectory fragments can be expressed as a set of several feature attribute vectors. These feature attributes can comprehensively express the local features of a trajectory fragment and the global features of user's moving behavior trajectory. In this section, the trajectory fragment is not simply the expression of coordinate information of the position information points, but extracts the speed, shape, position, rotation angle, acceleration, and other characteristic vectors from it. Using these eigenvectors, we can enhance the accuracy of analyzing the trajectory of user movement. We formally represent the trajectory fragment structure as follows: $\mathrm{TS} = (D, S, A, L)$. In addition to the above four features, we should also calculate the distance, time, and other features, using vector $W = \{W_D, W_S, W_A, W_L\}$ to represent the weight of the four feature vectors.

Since the weights of feature vectors correspond to the eigenvectors of the trajectory segments, their values should be greater than or equal to zero, and the sum of their weights should be 1; we can generally assume that the weights of all feature vectors are equal probability, and we can take the average value of 0.25 as the weights. Similarly, we can adjust the weights of each feature vector according to the sensitivity of the feature vectors of the trajectory fragments in the actual scene. For example, when analyzing the position-sensitive

Step 1: one by one, scanning the location information point sequence in the user movement behavior track;
Step 2: formula (5);
Step 3: formula (6);
Step 4: Set a threshold ω for corner θ, store the corner satisfying $|\theta| > \omega$ as a mutation point, and then divide the track segment according to the position information point of the corner. n is the number of sampling points, and the time complexity of the algorithm is $O(n)$.

Algorithm 1

trajectory fragments, we can focus on the position vectors, and the weights $W_D = W_S = W_A = 0, W_L = 1$ are also feasible.

According to the feature vector and its weight to complete the structural similarity comparison, mainly through the analysis of the differences between the feature vectors of the trajectory segments to complete the comparison [14], according to the definition of the trajectory segment structure, we can define two trajectory segments are $L_i, L_j, 1 \le i \ne j \le n$. The comparison function of two trajectory segments is $D(L_i, L_j)$, velocity vector is $S(L_i, L_j)$, angle vector is $A(L_i, L_j)$, and position vector is $L(L_i, L_j)$. The four comparison functions above constitute the calculation of structural similarity of the trajectory segments, as shown in the following Formulas (7) and (8). The function $N(\cdots)$ denotes the normalization of the distance. Because the range of each eigenvector in the trajectory segment is different, the normalization of the distance is the normalization of the distance of each eigenvector. The SSIM of structural similarity is represented by 1 minus the normalization of the distance:

$$S\left(L_i, L_j\right) = \left(D \times W_D + S \times W_S + A \times W_A + L \times W_L\right), \tag{7}$$

$$\mathrm{SSIM}\left(L_i, L_j\right) = 1 - N\left(S\left(L_i, L_j\right)\right). \tag{8}$$

The structural similarity comparison of trajectory fragments can express the structural differences of each trajectory fragment on the feature vectors. Therefore, the smaller the SSIM value of the trajectory fragments, the greater the SSIM value of the trajectory fragments. Moreover, the distance between the structural similarities of the trajectory fragments is symmetrical, that is, $\mathrm{SSIM}(L_i, L_j) = \mathrm{SSIM}(L_j, L_i)$. Therefore, it can be found that the method based on structural similarity can well reflect the structural differences between trajectory segments.

According to structural similarity, the direction information, speed information, angle information, and position information are compared [15].

(1) The direction vector comparison function $D(L_i, L_j)$ denotes the degree of similarity of two similar trajectory segment L_i, L_j in the direction of motion. As shown in Figure 3(a), φ is the angle between the direction of the trajectory, and the formula for calculating direction vector comparison function is as follows:

$$D\left(L_i, L_j\right) = \begin{cases} \left\|L_i\right\| \times \sin\phi, & \text{if } (0^\circ \le 90^\circ), \\ \left\|L_j\right\|, & \text{if } (90^\circ \le 180^\circ). \end{cases} \tag{9}$$

If two similar trajectory fragments have the same direction and the angle φ is small, the two trajectory fragments tend to be parallel in the same direction, which is called the best state, then the Dir Dist value approaches zero. If two similar trajectory fragments are in opposite directions and the two trajectory fragments with larger angle φ tend to be in reverse parallel, the worst condition is that the Dir Dist value is the length of the trajectory fragments involved in the comparison.

(2) The speed vector comparison function $S(L_i, L_j)$ expresses the trend of user mobility. The velocity vector comparison function is shown in Formula (10), where $S_{\max}(L_i, L_j)$ is $|V_{\max}(L_i) - V_{\max}(L_j)|$, representing the absolute value of the maximum velocity difference between the trajectory segments. Similarly, $S_{\mathrm{avg}}(L_i, L_j)$ and $S_{\min}(L_i, L_j)$ represent the absolute value of the difference between the average velocity and the minimum velocity, respectively. We can judge the difference of velocity vectors from the three aspects of maximum, minimum, and average velocity:

$$S\left(L_i, L_j\right) = \frac{1}{3}\left(S_{\max}\left(L_i, L_j\right) + S_{\mathrm{avg}}\left(L_i, L_j\right) + S_{\min}\left(L_i, L_j\right)\right). \tag{10}$$

(3) The angle vector comparison function $A(L_i, L_j)$ expresses the degree of eigenvalue change caused by the change of direction in the trajectory segment. As shown in Formula (11), where the angle of rotation θ is calculated according to Formula (6), the internal rotation angle is positive and the external rotation angle is negative, the angular distance of the trajectory segment is the cumulative value of many internal corners of the trajectory, and the direction of change within the trajectory segment can determine the value of each angle:

$$A\left(L_i, L_j\right) = \frac{\sum_{1,1}^{P(L_i), P(L_j)} \left(\left(\left|\theta_i - \theta_j\right|\right) / \left(\left|\theta_i\right| + \left|\theta_j\right|\right)\right)}{P\left(L_i\right) + P\left(L_j\right)}. \tag{11}$$

Figure 3(b) shows that if each corner of the two trajectory segments rotates to L_i and L_j matches, the value of the angle vector comparison function is 0, which is the best case. If the two trajectory segments turn to L_i and L_j in opposite directions, that is, the two trajectory segments are

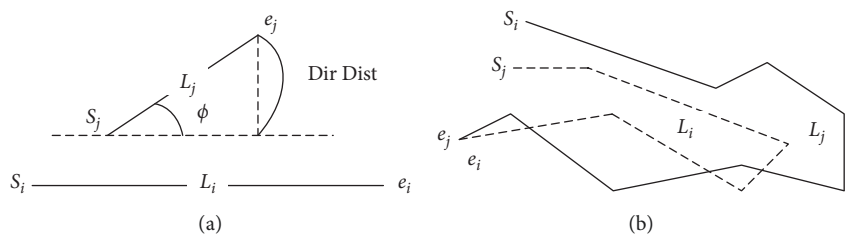

Figure 3: Comparison of track direction and rotation angle: (a) direction contrast; (b) corner contrast.

in opposite jagged shape, and the value of the angle vector comparison function is 1, this is the worst case.

(4) For the position vector comparison function $L(L_i, L_j)$, we can use Hausdorff distance to measure the location distance of the trajectory segment, as shown in the following formula:

$$L\left(L_i, L_j\right) = \max\left(h\left(L_i, L_j\right), h\left(L_j, L_i\right)\right), \tag{12}$$

where $h(L_i, L_j) = \max_{a \in L_i}(\min_{b \in L_j}(\mathrm{dist}(a, b)))$ is the direct Hausdorff distance between L_i and L_j, i.e., the maximum distance from a point in L_i to the nearest L_j and $\mathrm{dist}(a, b)$ represents the Euclidean distance function between points.

3.2. Similarity Computation of User's Mobile Behavior Trajectory. At present, we collect and store the trajectories of tourism users' mobile behavior, cluster the typical similar trajectories from these trajectory data, analyze the behavior patterns of user's mobile behavior trajectories, and predict the personalized needs of tourism users based on structural characteristics. Clustering analysis is to divide user behavior trajectory into several groups with high cohesion and low coupling. It requires high similarity of user behavior trajectory in the same group, and low similarity of user behavior trajectory in different groups. The goal of clustering analysis is to find out the trajectory data with the same or similar behavior patterns from the trajectories of some users' mobile behaviors, analyze the personal preferences, consumer demands, and behavior characteristics of the trajectories of tourism users' mobile behaviors, and accurately determine the similarity between trajectories of users' mobile behaviors. At the same time, the trajectories of users' mobile behaviors with high similarity are gathered into one class [16].

Most of the online travel users are in the same scenic spot, similar routes to carry out activities, and most of the resulting mobile behavior trajectory data have local similarity and global dissimilarity. It is difficult to find the personalized characteristics of tourism users by analyzing the complex and large number of users' mobile behavior trajectories and effectively extract users. The analysis of a part of the mobile behavior trajectory is more conducive to finding the information contained in it [17]. Therefore, the trajectory analysis method based on the whole trajectory in traditional research is easy to cause the inaccuracy of trajectory analysis. In this paper, we use structural features to calculate the similarity of user movement behavior. This method needs to calculate every corner of the user's mobile behavior trajectory and find the sampling point with larger rotation angle, which is regarded as the sudden change point of the user's mobile behavior, and then divides the trajectory segment by the sudden change point. In this way, the rotation angle of each trajectory segment obtained will not change significantly, and the trajectory structure tends to be stable. Then, a trajectory model of user's mobile behavior is constructed, which is characterized by trajectory direction, trajectory speed, trajectory angle, and trajectory distance. Taking these features as parameters, threshold values are set to express and adjust the weights of each feature according to the actual application scenarios, and a trajectory similarity algorithm is constructed to calculate the user's movement behavior. The object of this paper is to calculate the structural similarity of some trajectory segments which are divided according to the sudden change points of large turning angles by using the trajectory similarity algorithm constructed with structural features as parameters. It is used to judge the similarity degree of each user's moving behavior trajectory and then completes the feature analysis of user's moving behavior trajectory. The simulation results show that the trajectory similarity calculation algorithm is efficient, the weight adjustment of each structural feature is flexible, and the trajectory analysis results are more in line with the needs of practical application scenarios and have higher application value and practical significance.

On the basis of obtaining the feature vector distance of user's moving behavior trajectory segment, the trajectory segment with high similarity is analyzed, and then the clustering algorithm is used to complete the clustering of user's moving behavior trajectory. By comparing the structural similarity between the trajectory segments and other trajectory segments which are not on the same trajectory, a number of ε-nearest neighbor sets of trajectory segments are formed. The number of ε-nearest neighbor sets is used to determine the midpoint of trajectory segment clustering, and then the trajectory segment clustering is realized. A trajectory segment clustering algorithm based on structural similarity is constructed.

The steps of clustering algorithm based on structural similarity are given in Algorithm 2.

From the analysis of the above algorithms, it can be seen that, in the trajectory segment clustering algorithm based on structural similarity, it is very important to determine the

Step 1: first calculate the corner θ of each track segment sampling point P_i;
Step 2: according to the corner threshold ω, we divide the trajectory of user movement into TS of some track segments.
Step 3: calculate the distance between the trajectory feature vectors based on the weight of the trajectory segment feature vectors.
Step 4: calculate the ε-nearest neighbor set of the track segments with high similarity.
Step 5: the distance clustering segment is centred on the similarity track segment ε-nearest neighbor set.
Step 6: initialize clustering ID and track segment clustering markers.
Step 7: traverse the trajectory fragments, find the core clustering and set the clustering ID, and then add the pointers of these trajectory fragments to a new node in the index tree.
Step 8: determine whether the set center of ε-nearest neighbors meets the specified distance. If it meets the requirement, then add the cluster ID marker to the trajectory fragment, expand the clustering, construct the index tree node, and repeat steps 7 and 8 until all trajectory fragments are traversed.

Algorithm 2

threshold value of ω, ε-nearest neighbor, and the threshold value of σ nearest neighbor number, which can directly affect the time complexity and space complexity of the algorithm. It needs to be verified repeatedly and determined according to the actual application fields. Therefore, we mainly analyze the algorithm qualitatively.

Through repeated verification of the algorithm, in the data analysis of trajectory of travel user's movement behavior, the value of ω cannot be set too small, and if set too small, some characteristic details of trajectory segments will be lost. On the contrary, the value of ω cannot be set too large and cannot effectively identify the abrupt change point or sampling abnormality of the trajectory segment, which directly affects the structure of clustering analysis. Similarly, if the threshold value σ of the number of neighbors is set to be large enough, then no trajectory segment can satisfy the requirement of $|N_\varepsilon(L)| \geq \sigma$, and all trajectory segments will be marked as abnormal conditions. On the contrary, if σ is set too small, all the trajectory segments may become the clustering center, so that the trajectory segments will be self-contained and the number of clusters will be too large.

3.3. Discovery of Popular Tourist Attractions. By effectively identifying the location information points in the trajectory data of users' mobile behavior, the feature vectors of the trajectory segments can be extracted, and the semantics of these location information points can be expressed as the route, the scenic spots, and the behavior patterns of an online travel user in the past period of time. By clustering and analyzing the trajectory fragments containing location information points, we can find that the traveling users have a longer time in a certain area, which can be interpreted as the tourist users have a higher degree of interest in a certain scenic spot. Semantic expression is a popular tourist spot with longer stay time for online travel users. In practical scenarios, many traveling users will visit the same or similar scenic spots. From the trajectory of users' mobile behavior and the region of interest, traveling users with similar trajectory and the same region of interest can predict their similar preferences or similar behavior characteristics. These regions of interest frequently stayed by tourist users will appear as overlapping regions in the trajectory of user's mobile behavior. If these overlapping regions are found, the popular scenic spots concerned by tourist users can be found and the users who like these scenic spots can be clustered. And then, dig out the other characteristics of these users to complete the personalized tourist attractions recommendation of similar tourists. We extract the feature parameters of these overlapping areas, such as overlap time and overlap times, which can reflect the similarity between the traveling users. It can identify the tourist attractions that the tourist users are interested in during the mobile process and recommend the most likely popular tourist inventory for other tourist users who have a higher similarity with their user's mobile behavior trajectory, so as to tap the potential preferences of the tourist users [18]. Assuming that travel user A and travel user B share a higher degree of similarity in the trajectory of users' mobile behavior, it can be found that some scenic spots are visited by users A but not by users B. Through mining, it is known that these scenic spots may be of interest to users B. Then, we can recommend these scenic spots to B users through A users, so that these scenic spots become the potential and most likely scenic spots for B users to visit. We can also use the activity sequence to express the popular scenic spots that tourists often visit, and the trajectory of nearby tourists is more instructive [19].

In the process of analyzing mobile user behavior trajectory data with structured eigenvectors, it is not difficult to find that the moving speed of user behavior trajectory is not the same in different time periods, or it is slower in a certain time period, or it is faster in a certain time period. Figure 4 shows the moving speed of the user in different periods of time, in which the trough is formed during the period when the user moves slowly and the peak is formed during the period when the user moves fast, but both trough and peak can indicate the user's continuous generating activity. And, the slow moving trough time contains more user behavior characteristics, so this paper focuses on the behavior characteristics of mobile users in trough situation.

As shown in Figure 4, by comparing the speed, distance, and time of user's moving behavior trajectory, the structured features of mobile users and the behavior differences of tourist users can be clearly analyzed. We focus on the analysis of two dimensions: the speed and the time of the slower wave trough. As shown in Figure 5, the slower the traveling speed of the tourist user, or the less the change of

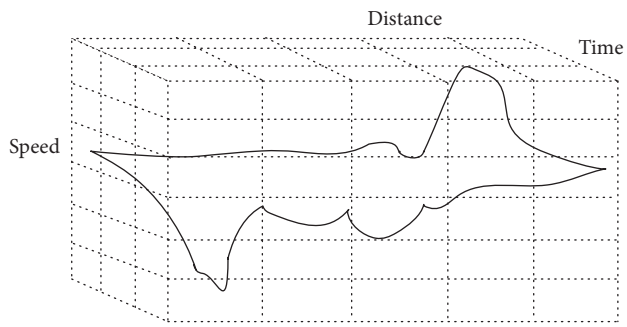

Figure 4: Mobile speed of user behavior trajectory.

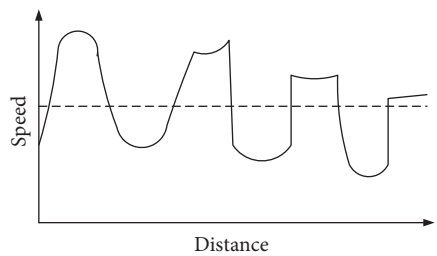

Figure 5: Two-dimensional trajectory analysis of user movement behavior.

the active area in a period of time, the most likely the predictable user behavior characteristic is; that is, the traveling user stays at a certain scenic spot for browsing, resting, or taking photos. The longer the trough, the more attractive the scenic spot is. The more tourists are staying at the same scenic spot, the more scenic spots can be designated as popular tourist attractions.

For example, when a tourist visits a scenic spot, he or she forms a trajectory of the user's movement behavior. Three troughs appear in the trajectory, indicating that the user may have experienced three scenic spots or rest areas, of which the first trough has a shorter experience. It shows that tourists spend less time visiting the first scenic spot, travel faster, continue to move forward at a faster speed after the tour, and spend a little more time watching the tide or taking pictures when they meet the scenic spot of interest. So tourists will slow down, move in a more fixed area, and travel at a slower speed, thus appearing the second trough period, after the tourists continue to move forward; when the formation of the third trajectory speed reached trough state, semantic expression may have two situations. The first is that the tourists reach a certain degree of fatigue or meet a rest area, stop and rest; the second is that the tourists arrive at a well-known scenic spot, gather more tourists, people will stay in a certain position, waiting for sightseeing and photography, moving slowly, and almost stop. The above two semantics can be distinguished by whether the location in the electronic map is a resting area or a scenic spot. However, in the actual tourist attractions, the situation may be more complicated. For example, a tourist is an outdoor sports enthusiast who has good physical strength and likes natural scenery. Because of his fast moving speed, there is little difference between the wave crest and trough of the waveform trajectory formed by the speed and distance. Although his tour speed is fast and his stay time is short, the location he stays in is still the area of interest. In this way, moving objects with similar frequencies in the velocity-distance waveform can be found not only in the known hot spots of the users, but also in the scenic spots that the potential users may be interested in, even in the preferences, occupations, and personality characteristics of the tourist users. It helps to gather tourists with similar preferences and similar personalities to achieve the confluence module [20].

Popular scenic spots refer to scenic spots with long staying time after arrival [21]. In the user's mobile behavior trajectory, the hot spots can be marked as $H = \{H_1, H_2, \ldots, H_n\}, H_j = \{L_i, L_{i+1}, \ldots, L_m\}$, H is used to denote a trajectory fragment. When the traveling user passes through a hot spot area with high interest and stays for a long time, the trajectory fragment moves at a speed close to or far below the normal trajectory speed. We can think that the tourist user has conducted a deep browsing in the scenic spot or some behavior activities have taken place in the scenic spot area. We can analyze the information such as the time of arrival, the time of stay, and so on. The region with dense user access points can be expressed as a popular tourist attraction area with high user access frequency [22].

Because GPS receiving equipment receives satellite signals in vast and open areas with high intensity and good positioning effect, satellite signals in indoor areas will be shielded by the wall, resulting in weak positioning signal and reduced positioning accuracy [23]. Therefore, when analyzing tourists' preference for scenic spots through the status of stay, it is necessary to distinguish between outdoor and indoor scenic spots. The positioning signal of outdoor scenic spots is good and has high precision. It can acquire the location information points at sampling frequency in real time and form the locus of user's movement with dense location information points. The positioning signal of indoor scenic spots is weak, which affects the positioning accuracy. Even when the signal is lost, the location information points cannot be obtained in time according to the sampling frequency requirement, and the space area of the indoor attractions is small, which makes some location information points overlap. This repetitive activity can also find that the tourists are visiting a certain indoor attractions regularly. The popular scenic spots are divided into two types: one is the outdoor scenic spots, such as natural landscape, gardens, playgrounds, and other broad areas, in a longer period of time, can obtain more dense location information points formed by the user's mobile behavior trajectory, recorded as HR_{II}; Another kind is indoor scenic spots, such as restaurants, shopping malls, tourist centers, and other closed areas, in a long period of time, may lose a certain location information point sampling information, but after leaving the area, they can get the location information point again, recorded as HR_I. Firstly, the trajectory data of user's mobile behavior are obtained by sampling the location information points, and then the trajectory data of user's mobile behavior is denoised. Finally, according to the characteristics of the location information points, the HR_I and HR_{II} popular scenic spots domain are divided by the density clustering method. The steps for finding popular scenic spots is given in Algorithm 3.

```
Input parameters: user movement behavior trajectory Q, minimum speed S, minimum time T, and maximum disturbance threshold
MT.
Output parameters: collection of popular scenic spots HR.
Step 1: for (i = 2, i ≤ |Q|, i++) /* |Q| represents the number of location information points*/
Step 2: D [i − 1] · T = cal T (p_i − 1, p_i);
Step 3: D [i − 1] · S = cal D (p_i − 1, p_i)/D [i − 1] · T;
Step 4: HR = {}; C = {}; CO = false;
Step 5: for (j = 2, j ≤ |T| − 1, j++) /*cycle search indoor attractions area HRI*/
Step 6: if (D [j − 1] · T > T and D [i − 1] · S < n * S) then
Step 7: C = {p_j − 1, p_j}; /*record location information point stay area*/
Step 8: if (not CO) then CO = true;
Step 9: else C = Update {p_j − 1, p_j}; /*merge the location information points closer to the collection HR*/
Step 10: else if (CO) then
Step 11: HR = {C}; CO = false; C = {} /*search outdoor attractions area HRII*/
Step 12: if (D [j − 1] · S ≤ S) then /*determine activity intensive areas*/
Step 13: C = {p_j};
Step 14: if (not CO) then CO = true;
Step 15: else if (CO) then
Step 16: last Index = look Ahead (MT, S);
Step 17: if (last Index ≤ j + MT) then
Step 18: for k = last Index downto j do
Step 19: C = {p_k};
Step 20: j = last Index;
Step 21: else if (time (C) > T) then
Step 22: HÈ = {C}; C = {}; CO = false;
Step 23: return HR;
```

Algorithm 3

Because the location information points sampled by GPS are affected by the factors of region, space, and weather, it is easy to have inaccurate positioning or interruption of positioning [24]. When the user enters the indoor scenic spots from the outdoor scenic spots, the short signal interruption will occur, and the positioning data receiving error will easily occur. In order to adapt this error, a maximum disturbance threshold MT is set in the hot spot detection algorithm to enhance the accuracy of location information points.

The outdoor and indoor scenic spots are divided according to the location information of popular scenic spots. The density-based hot spot discovery algorithm is used to retrieve two different types of user residence areas, outdoor and indoor, in the trajectory of user's mobile behavior, and define them as hot spots [25]. The algorithm has four input parameters: trajectory of user's mobile behavior, minimum speed, minimum time, and maximum disturbance threshold. Among them, the threshold of minimum speed is related to the activity speed of tourist users in the scenic spot area. If walking tour, the general speed is 2 to 3 meters per second. If the sudden reaction speed of the location information points slows down significantly, it indicates that the tourist users have arrived at the scenic spot area, and specific user behavior has taken place. On the contrary, if the sudden response speed of the location information points increases over a period of time, it indicates that the travel users have changed their behavior patterns. For example, we can leave the scenic spot and take a sightseeing bus to the next scenic spot, so we can set it according to the sampling time. There is no absolute fixed value in the setting of the minimum time threshold. Generally, if a tourist user stays in a certain area for more than 30 minutes, it can be considered that the tourist user arrives at a scenic spot or rest area, and changes in user behavior have taken place, resulting in a specific activity. The maximum perturbation threshold is only used to express the number of continuous perturbations when the abnormal location information points are sampled. If the number of abnormal location information points is smaller than the perturbation threshold, the abnormal sampling information points can be merged into the normal location information points of the user's mobile behavior trajectory data set. If the number of abnormal location information points sampled in the former HR is larger than the perturbation threshold, it is necessary to preserve the current user's mobile behavior trajectory and then detect the new hot spots after abnormal location information points sampled to form a new user's mobile behavior trajectory. The settings of the minimum time threshold and the maximum disturbance threshold are related to the sampling frequency of the location information points. In the popular scenic spot area detection algorithm, the trajectory of the user's movement behavior is traversed twice. The algorithm complexity is linear order $O(n)$. Among them, n denotes the number of location information points in the trajectory of the user's mobile behavior, and the algorithm can retrieve the hot spots with frequent activities.

4. Travel Recommendation Model

4.1. Application Scene

(1) *Tourist Attractions Recommendation*. In the mobile scenario where the user completes the tourist attraction tour, the tourist user will generate multi-dimensional information to realize the application scenario recommended by the tourist attraction, which can hide the rarely used dimensions. Focus on the user's city, mobile behavior trajectory in the corner location information points, hot spots and user behavior patterns and other dimensions, accurate analysis of user preferences, the same characteristics of the user recommend the most likely favorite tourist attractions [26].

(2) *Hotel Catering-Related Recommendation*. Tourist users need to visit other applications frequently in the process of touring, such as electronic map applications, O2O applications, restaurants, e-commerce, outdoor equipment, etc., a single visit to each application, users need to frequently exit one application login another application, will cause user inconvenience, inefficiency, etc. According to the application relevance assessment model, we analyze the application of tourism users' preferences. Establish the relationship between these applications, so that users can access a travel APP directly related to other applications they are used to daily life, making travel APP a personalized all-round service platform [27].

(3) *Tourism User Preference Content Recommendation*. Tourist users may often inquire about certain contents, such as outdoor equipment, fitness and health care, restaurants and entertainment, and surrounding scenic spots in the process of using the application. According to the content retrieval evaluation model, users can retrieve keywords, learn user preference content, and discover their hobby characteristics and behavior characteristics. According to these preferences, travel APP can construct a personalized interface for users, giving priority to the information, articles, and news that travel users are interested in [28].

4.2. Travel Recommendation System. With the combination of Bluetooth, WIFI, and other RF communication technologies and mobile terminal devices, mobile point-to-point communication environment has been derived, and many different research topics have also emerged. This research talks about the relationship between mobile attraction recommendation system and social software from the perspective of mobile social software and completes interaction through user comment sharing in mobile point-to-point environment. In this paper, an interactive system of tourism comment information sharing and social networking software is established, which includes three functions: recommendation, reunion, and comment. It is used to explore the interaction between users in mobile point-to-point environment. The preliminary test has been completed in this paper. The experimental results show that the recommendation, convergence, and comment functions of the system can provide precise services for users and provide a basis for further research on the wide application of user behavior trajectory in precise marketing.

This paper focuses on the problem of information sharing and social interaction of tourism mobile recommendation system in mobile point-to-point environment. The system mainly includes three functions: recommendation, convergence, and information sharing. In the recommendation function section, we assume that users will leave comments and other information after visiting a scenic spot. When other users meet with them, they can exchange comments through RF communication technology. These comments are calculated by system algorithm to recommend scenic spots that meet users' interests. In addition, users can also actively send requests to other people to join the information and find similar interests around users to visit a scenic spot. Of course, users can also actively share location, comments, traffic conditions, tourist density, and other related information.

In order to enable the interaction and sharing of information between remote users, the relay mode under mobile point-to-point can be adopted. Every user in the system plays the role of information transmission, that is to say, each user's mobile terminal is a relay node for information transmission and constantly transfers the information they have mastered to the users at a long distance.

4.2.1. System Architecture. The mobile peer-to-peer environment mainly transmits information through the direct transmission between peer-to-peer users and the relay mode assisted by the third party. Using this feature, the system proposed in this paper mainly provides three services: recommendation, convergence, and review. First of all, the main purpose of recommendation service is to recommend scenic spots similar to user's interests to users through user's evaluation information, so that users can have a reference direction for the next destination in the journey, so that users can travel more smoothly. Secondly, the convergence service allows users to initiate a convening activity, gather other interested users around, visit the scenic spots together, or buy specialty goods together, through group buying to get a better price, or to strive for preferential services. Thirdly, evaluation services are divided into general information and specific information. General information is simply the transmission of personal information and specific information, so that the use of convergence services conveys the convening activities of the department of the offensive, through short messages, and the expression of personal information is incompatible; specific information is only for convening activities issued information. To provide the above services, the system architecture is presented in Figure 6.

(1) Interface Module. This module is responsible for the user and the system function docking; through this module, the system function interface is expressed and the user is guided to carry out the operation of various functions.

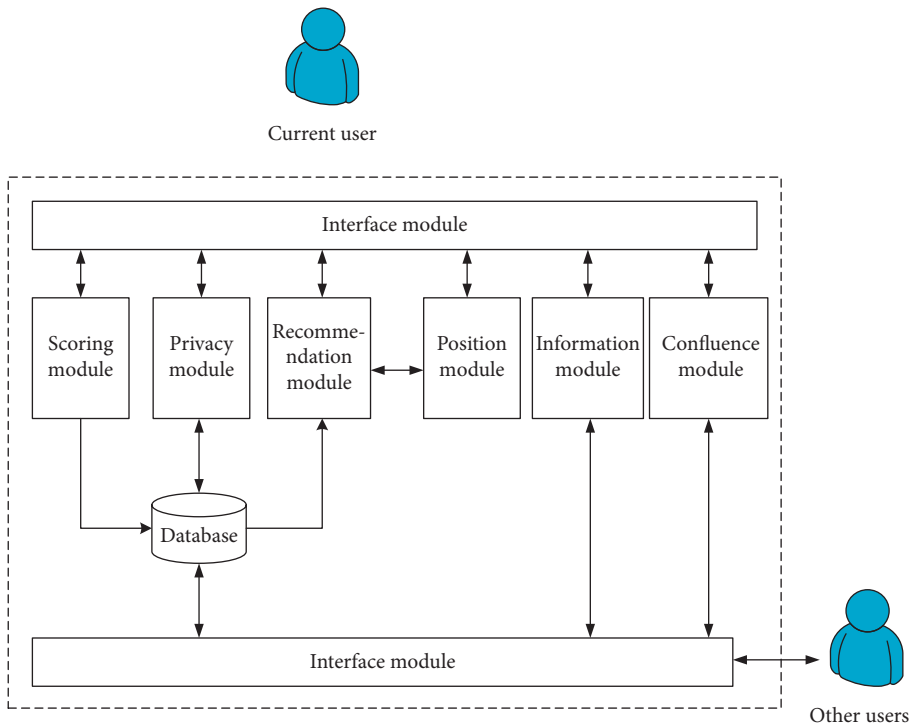

Figure 6: Mobile point-to-point tourism recommendation system architecture.

(2) Scoring Module. At present, the commonly used recommendation system is based on the scoring mechanism, which collects user's scoring data to calculate and provide recommendation services. The scoring module proposed in this study is mainly responsible for recording the user's evaluation of scenic spots. At the initial stage, the recommendation system often faces the problems of incomplete user scoring information, too many items not scored, and the difficulty of calculation caused by the noise of data, resulting in the decline of recommendation accuracy. Therefore, this study classifies scenic spots, requires users in the initial stage, must be based on the type of scenic spots scoring to ensure that individual users in the initial stage, and needs to score for the type of scenic spots to ensure that individual users' scoring information has been scored by the common column.

(3) Transport Module. Because this research system is built in the mobile point-to-point environment, user scoring, information, and other need to be obtained and transmitted through the transmission function; this study uses Bluetooth transmission technology to achieve the transmission of related functions. This module enables the system to automatically exchange scoring data through Bluetooth without interfering with the user when they meet, so as to achieve the purpose of collecting data. In terms of scoring exchange mechanism, this study currently uses unlimited scoring exchange method, when users meet, the exchange of all the scoring data held by both sides. However, information that has not yet been scored is not helpful to the recommendation system. Therefore, in the scoring exchange module, it is assumed that only the user has scored more than five scenic spots before the exchange, while the other scoring data obtained by others is more than five items before passing on to other users. On the other hand, the transmission module has the search function and can discover other users around the user; when the user wants to pass its ideas to the surrounding users, it can be completed through this module.

(4) Recommendation Module. This study analyzes the recommended operation by exchanging accumulated score data. This recommendation module uses collaborative recommendation and Pearson correlation coefficients to perform recommendation operation. The formula is shown in (13). Suppose that $U(i,a)$ is used to predict the possible degree of preference of i to a scenic spots. $F_j(a)$ is the score of user j for a attractions and $\overline{F_i}$ is used to score the average score of holder i. $\overline{F_j}$ is the average score of user j, and $\text{sim}(i, j)$ is the similarity between user i and user j calculated by Pearson correlation coefficient:

$$U(i,a) = \overline{F_i} + \frac{\sum_j \text{sim}(i,j) \times \left|F_j(a) - \overline{F_j}\right|}{\sum_j \text{sim}(i,j)}. \quad (13)$$

In the process of recommendation, the recommendation module first calculates Pearson correlation coefficient, calculates the first 20 items of scoring data which are most similar to users, and then runs the subsequent recommendation algorithm. Finally, the user's predicted value of a certain scenic spot is obtained by weighted average of these scoring data and similarity, and five scenic spots with the highest predicted value are recommended to users for reference.

(5) Position Module. This module can use Bluetooth GPS receiver to receive satellite signals and select the local latitude

and longitude values to determine the location of the user. Finally, combined with the processing results of the recommendation module, the electronic map shows the location of each recommendation site and the location of the user.

(6) Information Module. The concept of user's active comment can be added in the system; through the transmission of information, users can express their personal ideas to other users around. Adding the function of transmitting information in this part, the user can not only transmit the new information but also transmit the received information to other users in the transmission range.

(7) Convergence Module. Since the system is designed in a mobile peer-to-peer environment, a mobile convergence function is derived from the concept of mobile social networks. Through this function, travelers can dynamically search for other users with the same goals and preferences. Through the transmission of information, travelers can share the requested information to the surrounding users and thus find travelers willing to act together.

(8) Privacy Module. One of the focuses of mobile social software is to explore the interaction between users, but not everyone is willing to interact with others, so this study adds privacy considerations. This module can provide users whether to allow all other users or only allow some friends to search their own location through the system; through the privacy settings, users can not be disturbed by other users to carry out system operations but also to observe whether there is a willingness to interact between users.

J2ME can be chosen as the development platform of the system, and Bluetooth technology is the basic wireless transmission technology commonly available in mobile terminals. Therefore, it is feasible to use Bluetooth technology as a transmission tool. In order to expand the scope of information transmission, WIFI wireless network can also be considered as a transmission medium, which can effectively solve the problem of short transmission distance and unstable signal of Bluetooth.

5. Conclusion

Advanced GPS devices enable people to record their location histories with GPS trajectories. The trajectory of users' mobile behavior means to a certain extent that a person's behavior and interests are related to their outdoor activities, so we can understand the users and their locations and their correlation according to these trajectories. This information enables accurate travel recommendations and helps people to understand a strange city efficiently and with high quality. By measuring the similarity of different user location histories, the similarity between users can be estimated and personalized friend recommendation can be realized. The user stereoscopic user portrait can be portrayed through the integration of user movement behavior trajectory and social information. This paper takes the trajectory data of tourism users' mobile behavior as the research object and constructs the tourism precise marketing model. In the process of obtaining the trajectory of user movement, the characteristics of mobile user behavior track data are taken into account. The sensitivity of various features in the trajectory analysis process is adjusted by weight. The structured feature vectors and popular scenic spots discovery methods of user's mobile behavior trajectory are fully studied by clustering and collaborative filtering techniques, which lay a foundation for constructing the application model of tourism precision marketing.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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