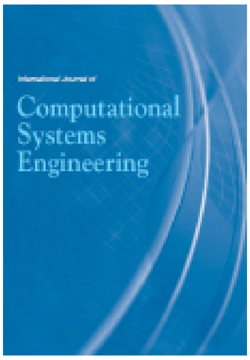

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Social network user browsing trajectory detection based on soft computing to promote a healthy environment

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Abstract: In order to improve the detection ability of browsing trajectory data for social network users, a mobile computing based method for detecting browsing trajectories of social network users is proposed. The study first utilises fuzzy logic to establish a social network user browsing trajectory data detection model. Then, the fuzzy parameter recognition method is used to extract the features of the browsing trajectory data of social network users. Finally, a social network user browsing trajectory detection method was designed by combining random forest learning algorithm and matched filtering detection method. The experimental results show that the method has a good output signal-to-noise ratio to eliminate redundancy, with a maximum redundancy elimination of 23.7 dB. The accuracy and stability are high, up to 93%, and it has a good detection effect on the browsing trajectory of social network users.

Keywords: soft computing; social networks; trajectory similarity; browse track; random forest; environment; social media.

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1 Introduction

With the continuous increase of the scale of social networks, social network user browsing trajectory mining has attracted people's attention. By analysing the characteristics of social network user browsing trajectory, combined with the optimised recommendation algorithm, the preference of social network user browsing trajectory is evaluated, so as to further promote the development of social networks (Liu et al., 2020; Almaatouq et al., 2020). In the process of mining social network users' browsing trajectory features, it is disturbed by redundant information, resulting in large redundancy (Qin and Zhao, 2021) and poor anti-interference (Bi, 2021). It is necessary to build an optimised social network users' browsing trajectory feature mining model, combined with optimised data mining and information fusion algorithm, Improve the ability of social network users to detect and recommend browsing tracks.

Rahimi et al. (2021) proposed a context location recommendation method, called CLR, which uses historical check-in and context information to learn the user's intention and spatial response to various context triggers. CLR starts with covariance analysis to reduce the dimension of check-in data, and then uses a random walk with an optimised version of restart to extract hidden user responses to context triggers. The potential factor model is established by tensor decomposition to predict the user's intention response under a given context trigger condition. Estimating the probability distribution of the user's location and the popularity probability of the location under the context setting allows the context space component to determine a set of matching locations that the user can access based on the user's intention response. These locations can be accessed by the user. The experimental results show that the accuracy of CLR recommendation is improved by 35%. However, the accuracy of this method needs to be improved. In Li et al. (2020), authors believe that the privacy disclosure of users is closely related to the privacy disclosure of surrounding users, but the relevant users studied in the previous methods are incorrect. This is because social networks reflect the homogenisation phenomenon that occurs in complex networks. To put it another way, it's possible that the assessed user group isn't connected to the privacy disclosure made by the target user. Due to the time-sensitive nature of private information, it is possible that the information stored by users who are no longer in the same context as the person being targeted is no longer accurate and has therefore lost its value. If we take the example of students and members of the working class, we can see that if they go to a different school to finish their education or change professions, the majority of the knowledge they possess will undergo significant transformations. This lack of timeliness has a crucial impact on the effectiveness of social network analysis and privacy protection, but researchers have not solved this problem. Therefore, this method studies and describes this problem, adds user behaviour tracking to solve this problem, and measures the user's privacy state more accurately. However, the feature recognition ability of this method is not strong in the process of social network user browsing trajectory data detection. Kamal et al. (2020) presented a technique for automatically discovering social networks using historical patient trajectory data called 'trajectory linking.' In this approach, the connection between patients is established based on their closeness to one another in space and their time frame. The findings indicate that using trajectory linking rather than just integrating patient data may provide a social network model with a higher degree of connectivity. The trajectory link model is able to depict the genuine state of the patient relationship when social network analysis is performed. However, the anti-interference performance of this approach is weak when it comes to the redundant processing of the browsing trajectory data of users of social networks.

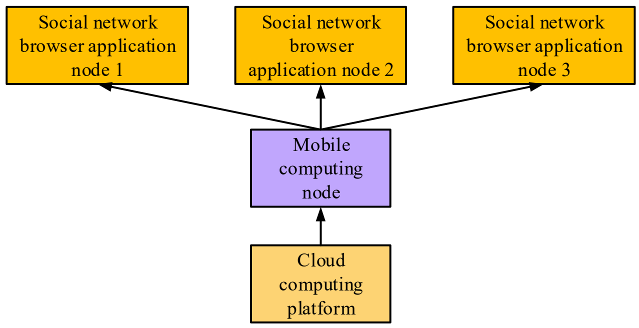
In order to solve the above problems and improve the detection effect of social network user browsing track data, this paper proposes a mobile computing based social network user browsing track data detection method. First, build a detection model of social network user browsing track data, and then combine autocorrelation feature matching method, random forest learning algorithm and matched filter detection method to achieve redundant filtering of social network user browsing track data. Finally, the effect of the design method is tested by simulation, in order to provide some help for improving the detection effect of browsing track data of social network users through this study.

2 Analysis of browsing trajectory data of social network users

2.1 Social network user browsing trajectory data detection model based on mobile computing

In order to ensure that the data used for social network user analysis comes from a healthy and positive environment, the following measures have been taken to ensure a healthy environment for users: firstly, identifying unhealthy content. By analysing the content that users browse on social networks, negative content and viewpoints related to health issues can be identified. If these contents are found to appear frequently on social networks, measures need to be taken to address them. Secondly, it is to promote health information. Social networking platforms can actively promote some health-related information and activities, such as regularly publishing health information, providing online fitness courses, and recommending healthy diets. These information and activities can help users better understand health knowledge and encourage them to adopt healthier lifestyles. Finally, monitoring user behaviour can reveal patterns of behaviour related to health issues by monitoring their behaviour on social networks. At present, social network activities and issues related to health mainly include mental health issues, unhealthy lifestyles, and the spread of false information. The structure of the social network user browsing trajectory data detection model based on mobile computing (Gopalakrishnan et al., 2020; Merlo et al., 2021) is shown in Figure 1.

Figure 1 Social network user browsing trajectory data detection model based on mobile computing (see online version for colours)



There are three nodes in the social network user browsing trajectory data detection model based on mobile computing: cloud computing, mobile computing, and social network browser application nodes, as shown in Figure 1. Basic nodes of social network applications are installed on terminal devices, and one of them is the social network browser application node. Using the mobile computing node, the cloud computing platform may access information from the social network terminal device, and the social network browser application node is primarily responsible for collecting that data. The edge node and the social network browser application node are connected through a communication channel established by the browser application. The mobile computing node acts as an intermediary hub when interacting with the cloud computing platform. This design simplifies the traffic of social network browser application nodes, and makes full use of the advantages of efficient data transmission of mobile computing nodes. Improve real-time data transfer and reduce transmission latency by using a mobile computer node (Feng et al., 2020). As a result of the use of mobile computing nodes, social network data may be securely sent and analysed.

Through relevant research, it has been found that in the process of collecting social network user data, the research on soft computing based social network user browsing trajectory detection and promoting healthy environment construction highly values the protection of user data and privacy, and considers multiple important ethical issues. The main ethical issues to consider include privacy infringement, misleading users, data discrimination, cyberbullying and harassment, information overload and distraction, information security risks, algorithmic bias and discrimination, and information manipulation and misleading. These issues may have an impact on the rights and privacy of users. Therefore, in order to ensure the rights and interests of users, the research team followed principles such as informed consent, minimal data collection, data anonymisation, data security, transparency and auditability, feedback mechanisms, and responsible research. These measures help ensure the ethics of research and the protection of user privacy, and promote the construction of a healthy environment for social networks.

2.2 Data mining of browsing trajectory of social network users

Principal component analysis (PCA) is a commonly used data analysis method for identifying and evaluating browsing trajectories of social network users. Through PCA, multiple variables can be transformed into a few principal components, which can reflect the vast majority of information about the original variables. In the process of identifying and evaluating browsing trajectories of social network users, PCA first analyses browsing trajectories through data dimensionality reduction. In the browsing trajectory of social network users, multiple dimensions of data are usually involved, such as user behaviour, content types, timestamps, etc. Through PCA, these multi-dimensional data can be reduced in order to better understand and analyse user browsing trajectories. Generally, data information loss occurs when data is dimensionally reduced. The loss degree of data can be controlled through PCA algorithm (Malan et al., 2020; Li and Youn, 2021). This algorithm protects the dimensionless data according to the correlation of the data itself. The detailed calculation steps are as follows:

Assume that the data matrix is defined as $k = (k_1, k_2, \ldots k_n)$, and the mean values of $k_j \in Q^T$ and k are expressed as $\bar{k} = \frac{1}{n}\sum_{j=1}^{n} k_j$. After k-means, PCA extracts major feature components. It analyses the distribution pattern of data samples in high-dimensional space and uses the highest variance as the discriminant vector to minimise data dimension. Function objective:

$$p = M^T k \ s.t. M^T M = R \tag{1}$$

where, the data conversion matrix is expressed as M, its $M \in Q^{r \times r'}$, and the data matrix k are converted through the data conversion matrix $M \in Q^{r \times r'}$ to obtain a new dimension space, whose dimension is expressed as r', the new dimension space is expressed as p, and the unit matrix is expressed as R.

In the above formula, PCA algorithm and the KL transformation (Lee et al., 2021) must be used in combination to solve matrix M, and the optimal features must be obtained through linear transformation before being used to reconstruct the training data according to the features. The mean square error before and after reconstruction must be restricted in order to minimise the error. Assume that the linearly independent vector is defined as $\delta_1, \delta_2, \ldots, \delta_m$, which is any n linearly independent vectors in n dimension. The matrix based on this is expressed as $\mu = (\delta_1, \delta_2, \ldots, \delta_m)$, the random variable in dimension is expressed as , and the random variable can be expressed by the above matrix $\sigma = \sum_{j=1}^{m} m_j \delta_j = \mu m$.

In the above formula, the weighting coefficient is expressed as $m = (m_1, m_2, \ldots, m_n)^T$, and the transformation coordinate from σ to m is expressed as μ. according to the vector value of m in KL transformation principle, the following calculation formula is obtained:

$$m_j m_l = \begin{cases} \kappa_j, & i = l \\ 0, & else \end{cases} \tag{2}$$

when the correlation matrix of σ is set as L and the value of L is known, that is:

$$L = \sigma\sigma^T = \mu m(\mu m)^T \tag{3}$$

Generally, the known data information is represented by σ. It can be seen from the above that L is known. When $\mu\mu^T = R$, R is a single matrix, which is defined as:

$$L\delta_j = \kappa_j \delta_j \tag{4}$$

In the above formula, the positive definite real matrix is L, and the eigenvectors corresponding to the algebraic eigenvalues of L and L can be defined as δ_j and κ_j respectively. Since the unit orthogonal matrix is δ, $m = \mu^T \sigma$.

The feature vector in front of m must be chosen when KL conducts the dimension reduction transformation, and the number of picked vectors is written as n after selection. Subsequently, the remaining feature vectors must be eliminated, which allows equation (2) to be changed into:

$$\sigma = \sum_{j=1}^{n'} m\delta_j + \sum_{j=n'+1}^{n} m\delta_i \tag{5}$$

The useful information retained after the residual vector is eliminated is expressed as $\hat{\sigma} = \sum_{j=1}^{n'} m\delta_j$. The calculation formula of the mean square error before and after the feature vector is eliminated is as follows:

$$v^2 = \sum_{j=n'+1}^{n} \kappa_j \tag{6}$$

Where, if the sum of eigenvalues corresponding to $n–n'$ eigenvectors is the smallest, then the mean square error is the smallest. When the eigenvectors corresponding to the maximum eigenvalue are n', the matrix of $n–n'$ is expressed as $\mu_{n'}$, and its $\mu_{n'}$ can replace μ, i.e., $m_{n'} = \mu_{n'}\sigma$, where the principal component obtained by dimensionality reduction of σ is $m_{n'}$.

Represent the covariance matrix corresponding to x in equation (1), that is:

$$E = \sum_{j=1}^{n} \left(k_j - \bar{k}\right)\left(k_j - \bar{k}\right)^T = kk^T \tag{7}$$

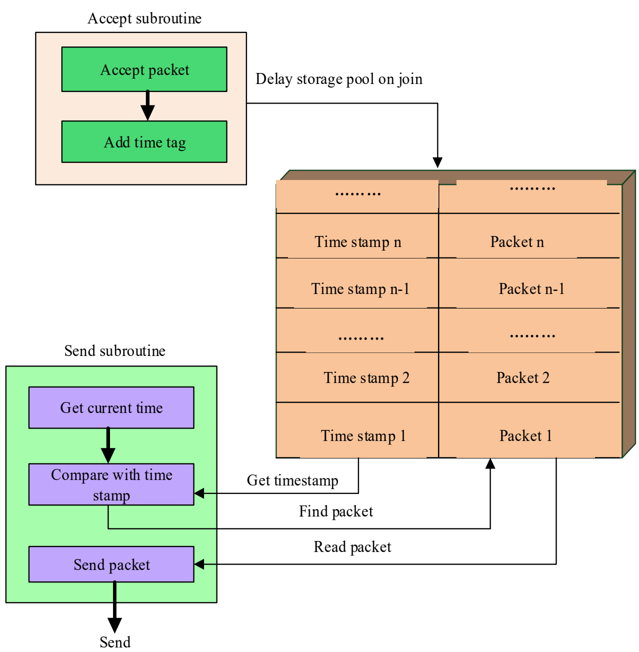
The matrix solution of M in equation (1) can be realised by the eigenvector corresponding to the eigenvalue of E. the eigenvalue and eigenvector of E are solved as follows:

Firstly, the eigenvalues and eigenvectors of the transpose matrix of E are solved. Let the eigenvalues and eigenvectors of k^Tk be κ_j', δ_j' and $\mu' = \mu_1'$, μ_2', …, μ_n') respectively, that is, the dimension reduction of the data is completed by obtaining the corresponding relationship between the eigenvalues and eigenvectors between the conversion matrices of E and E, that is:

$$\begin{cases} \kappa_j = \kappa_j' \\ \mu = k\mu' \end{cases} \quad j = 1, 2, \ldots, n \tag{8}$$

Combined with the dimension reduction processing results of social network user browsing trajectory data, the implementation structure of social network user browsing trajectory data mining is obtained, as shown in Figure 2.

Figure 2 Implementation flow chart of data mining for browsing trajectory of social network users (see online version for colours)



As we can see from Figure 2, this paper receives data packets in the receiving subroutine and adds time tags, then adds these data to the time delay storage pool for time stamp marking, and then sends the marked data to the subroutine. After obtaining the current time, it compares it with the time stamp, obtains the comparison results, and then finds and matches the data packets, and then sends the found data to the mail, this completes the design of data mining implementation process for social network users' browsing trajectories. PCA is suitable for identifying and evaluating browsing trajectories of social network users, mainly because it can effectively process high-dimensional data, reveal data structures, highlight main variables, have objectivity and interpretability, and dynamically capture data changes. By combining with other methods, PCA can provide more in-depth analysis of user browsing trajectories, providing valuable insights and suggestions for optimising social networks. After obtaining the current time, it is compared with the timestamp to obtain the comparison result. Then, the data packet is searched and matched, and the found data is sent to an email. This completes the design of the implementation process for social network user browsing trajectory data mining.

2.3 *Feature extraction of browsing trajectory data of social network users*

Based on the above process, the user's browsing interest information is obtained by observing the user's browsing habits. The user characteristic behaviour model is established according to the obtained information, and the specific implementation process is as follows:

First, establish their own statistical trajectory datas for users, then browse each trajectory data in turn, and establish the index method of the trajectory data by the collection of specific words described in each browsing text (Sanchez-Gomez et al., 2020). In order to represent the proportion of specific words in the trajectory data, add a numerical weight to all words in the user browsing text space. The numerical weight can also be regarded as the coordinate information of the word in trajectory data d in trajectory data space (Qin et al., 2019). In other words, a trajectory data d browsed by the user is regarded as any coordinate point in trajectory data space, so d can be described as a vector from the initial point to any point in trajectory data space. An important problem of trajectory data representation is how to add weights to the words describing the trajectory data.

At present, the commonly used method of adding weight is *tf***idf* -weighted scheme. *tf* indicates the number of times a specific word appears in a web trajectory data. Because the content of each trajectory data is different, the value of is also different in each trajectory data. The main function of *tf* is to determine the importance of this specific word in Web trajectory datas. *idf* represents global statistics, and the distribution law of specific words in the whole web trajectory data can be judged by referring to the value of *idf*. *idf* is set to $In(N/n)$, N represents the number of trajectory datas contained in the web trajectory data collection, and n represents the number of trajectory datas containing a specific word. The number of trajectory datas containing a specific word is negatively correlated with the value of *idf*, that is, the more trajectory datas containing a specific word, the smaller the value of *idf*. When all trajectory datas in the web trajectory data collection contain a specific word, the value of *idf* is 0.

For the web trajectory data information browsed by users, this paper uses the vector based method to describe it. The i element corresponding to the description vector V of trajectory data d can be calculated by the following formula:

$$w(d,i) = tf(i,d) * idf(i) \tag{9}$$

where, $tf(i, d)$ represents the result of word frequency statistics, that is, the number of occurrences of word w_i in web trajectory data d is:

$$idf(i) = In(N / n) \tag{10}$$

In the network big data system, if the user's evaluation feedback on the retrieval results is directly obtained, it is called explicit feedback. This feedback result cannot objectively evaluate the results of web browsing, and it is difficult to provide objective data for the construction of subsequent user behaviour characteristics model, reducing the usability of the model (Zhu et al., 2020). Different from explicit feedback, implicit feedback only evaluates the usability of the trajectory datas viewed by the user. This method will not affect the user's web browsing behaviour, but judge the user's browsing habits according to the user's browsing behaviour, so the result accuracy is high.

Generally, the browsing trajectory data is generated by browsing the web browser and network resources (Saverimoutou et al., 2020). The web browser provides an interface for users to browse and process trajectory datas. In the browsing process, the user's browsing behaviour reflects the degree of interest in the target trajectory data. These information can be collected to establish the user behaviour characteristic model. Users' browsing behaviour can be divided into the following types: review behaviour: Sliding scroll bar (*sl*), web browsing time (*rt*); reference type: follow hyperlink; retention type: retain web trajectory data (*sd*), print web trajectory data, add label, etc. By analysing the browsing behaviour of the above users, we can determine the user's interest in the current page. In order to more accurately distinguish the user's interest reflected by these browsing behaviours (Wang and Wang, 2020), each browsing behaviour v is given a corresponding weight C_v, and the user's interest in the current page is inferred by calculating the weight. The calculation formula is as follows:

$$R_i = \sum_{v \in F} C_v f_v(di) \tag{11}$$

where $f_v(di)$ is a binary function. When it is checked that the user has generated browsing behaviour v for the current page, the function value of $f_v(di)$ is 1, otherwise it is 0. The calculation results of R_i will be applied to the creation and update of user behaviour feature model.

Mining the semantic association feature quantity of user browsing track data, using the constraint cost factor as the feature function, the difference recognition function of browsing track data mining is obtained as follows:

$$h(x) = R\sum_{i=1} (\beta - \beta^*) K(y_i) + \gamma \tag{12}$$

where, β and β^* respectively represent the statistical feature quantity and edge information feature component of social network user browsing trajectory data mining, $K(y_i)$ represents the fuzzy kernel function of social network user browsing trajectory data De redundancy mining, and γ represents the recommended threshold of social network user browsing trajectory data mining.

The similarity feature diversity method is used to obtain the random dispersion feature component of social network user browsing trajectory data. Define C_i as the node set of social network user browsing trajectory data in directed graph q_i, and set:

$$C_i = h(x) - k\sum_{i=1} \lambda q_i \big/ r + l \tag{13}$$

where, r represents the feature distribution length of social network user browsing trajectory data mining, k represents the identification parameter, l represents the instantaneous time frequency of social network user browsing trajectory data mining, and λ represents the feature identification. Using fuzzy parameter identification (Garg et al., 2020), it is obtained that the reliability characteristic parameter of social network user browsing trajectory data mining is A, and then the probability density function of social network user browsing trajectory data detection at time t is:

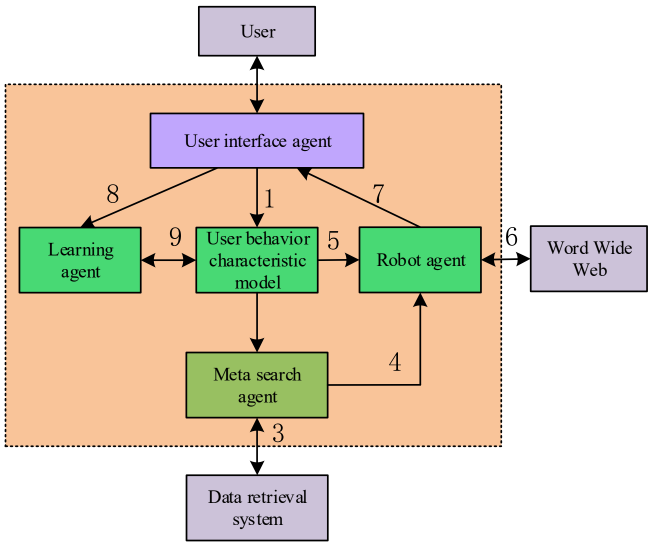
$$P_i(t) = \sum_{i=1} \frac{A}{C_i} Rj \tag{14}$$

Among them, j represents the feature extraction result of social network user browsing trajectory data mining, combined with autocorrelation feature matching method to realise data De redundancy detection. In summary, the digital weight method for feature extraction can effectively distinguish irrelevant information in social networks and find healthy browsing information through methods such as data pre-processing, feature selection, weight calculation, information filtering, and health information recommendation. Firstly, pre-process the raw data to remove noise and irrelevant information. Then, select the features that are most relevant to healthy browsing behaviour and calculate the weight of each feature. By comparing the weights of features, identify features that are not closely related to healthy browsing behaviour, and filter them as irrelevant information. Finally, based on weight analysis, recommend information highly relevant to healthy browsing behaviour to users. In addition, the digital weighting method is a dynamic process that can adjust the weights of relevant features with changes in user behaviour and content, continuously identify and recommend healthy information, and promote the construction of a healthy environment for social networks.

3 Data De redundancy processing and optimisation of test results

According to the above detection results, based on VSN model and user behaviour characteristics, the user personal information retrieval system (infoAgent) is jointly developed by combining meta search engine and agent technology. Build a user behaviour feature model to ensure that the information reflected by the model is closest to the needs of users, so as to make the data provided by the whole feature model accurate and speed up the retrieval efficiency. InfoAgent is mainly composed of user interface agent, robot agent, learning agent, meta search agent and user behaviour feature model, as shown in Figure 3.

Figure 3 Overall architecture of InfoAgent (see online version for colours)



InfoAgent

1 Create and save the user behaviour characteristic model q according to the user's browsing habits, and update the content in the model in real-time according to the user's different browsing behaviours.

2 The feature items with non-zero ownership value in the user behaviour feature model are filtered out and transmitted to the meta search agent as search keywords.

3 After receiving the feature items, the meta search agent sends a query request to other information search systems at the same time, and adds all qualified feature items to the URL list.

4 Feature items are extracted from all trajectory datas added to the URL list to form the feature vector of the trajectory data.

5 The extracted feature vector is pattern matched with the user behaviour feature model q, and the correlation is calculated.

6 Compare the correlation degree between the feature vector and the user behaviour feature model q with the specified minimum correlation degree R_{min}. if the value of the correlation degree is greater than R_{min}, take the URL as the starting point, issue instructions to robot R_{min}, conduct heuristic search on the model, and conduct pattern matching on all trajectory datas.

7 The trajectory data d that best matches the search results with the user behaviour feature model q is displayed to the user.

8 Continuously observe the user's browsing behaviour, and calculate the user's relevant feedback value according to equation (15).

$$f(i) = \sum_{b \in B} c_b f_b(d) \tag{15}$$

where c_b represents the weighting factor of the feedback behaviour.

9 According to equation (16), the user behaviour characteristic model is updated in real-time. Repeat operation step (2) until the user retrieval is completed.

$$w_{qk} \leftarrow w_{qk} + \beta \cdot f(d) \cdot w_{ik} \tag{16}$$

where $f(d)$ represents the user's feedback result to d, w_{dk} represents the weight of the k^{th} eigenvalue of d, w_{qk} represents the weight of the k^{th} eigenvalue in q, and β is the learning factor.

3.1 *Random forest learning algorithm*

The random forest learning algorithm is used to realise the convergence learning control of social network users' browsing trajectory data. The matching degree between the nodes of the feature distribution of social network users' browsing trajectory data and the feature points of semantic similarity is analysed. The random forest learning process of removing redundancy of social network users' browsing trajectory data is as follows:

$$N = 1 + \ln(P_i(t)) \tag{17}$$

The multi-attribute decision-making method is used to obtain the characteristic component of social network user browsing trajectory. In the intuitionistic fuzzy environment, the random forest learning method (Lee et al., 2019) is used to obtain the learning convergence control function of social network user browsing trajectory data mining. Based on the feature mapping analysis results of social network user browsing trajectory data, the random forest learning is adopted to obtain the de redundant filter function of social network user browsing trajectory data:

$$H = u(t) \exp\left[N\left(t - t_0\right)\right] \tag{18}$$

where, $u(t)$ is the learning convergence control function (Du et al., 2021), and t_0 is the de redundancy time of social network users' browsing trajectory. Calculate the matching degree of redundant nodes and associated words of user browsing track data, and filter the data redundancy information according to the random forest learning results of user browsing track data.

3.2 *Filtering redundant information of browsing trajectory data of social network users*

The random forest learning algorithm is used to realise the convergence learning control of social network users' browsing trajectory data. Combined with the matching filter detection method, the redundant filtering of social network users' browsing trajectory data is realised.

According to the correlation between membership and non-membership, the return state w of social network user browsing trajectory data filtering is obtained, and the redundant information output detection sequence is obtained.

Using the shape similarity feature analysis method, the training sample set is obtained. Let the evolution feature filtered from the browsing trajectory data of social network users be ξ_i, according to the random forest learning results, the optimised data filtering objective function is obtained as follows:

$$minimize = \frac{1}{2}w^2 + H\sum_{i=1}(\xi_i) \tag{19}$$

where, ξ_i represents the minimum grey correlation information. According to the fuzzy multi-attribute decision-making results, the hybrid kernel function of redundant filtering of social network user browsing trajectory is obtained, and its expression is:

$$K_{\min} = {}^{\beta}\!/_{H} + K_{poly} \tag{20}$$

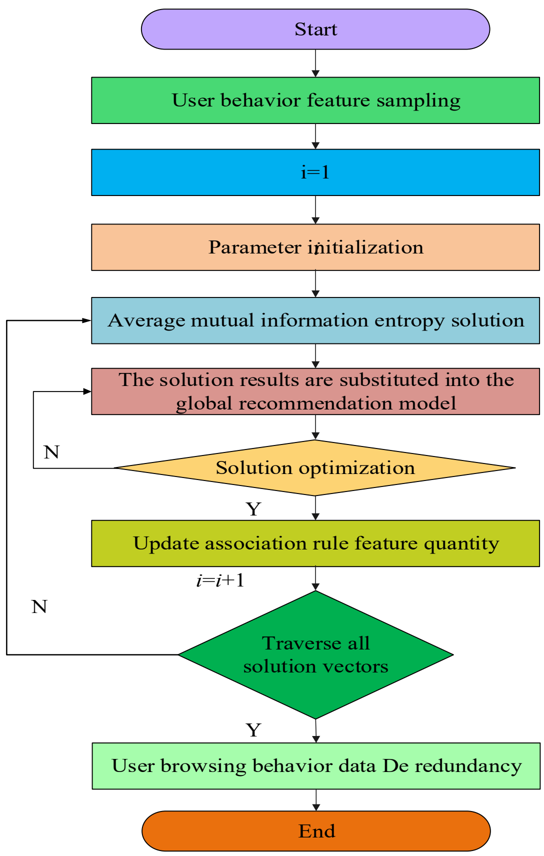
where, K_{poly} represents the preference kernel function of social network user browsing trajectory data mining, extracts the constitutive feature of social network user browsing trajectory data mining, and obtains the decision function of membership set as follows:

$$Q = K_{\min} \times m(z) \tag{21}$$

where, $m(z)$ represents the user item score value of social network user browsing trajectory data. According to the above analysis, combined with the matched filter detection method, the redundant filtering processing of social network user browsing trajectory data is realised, and the research on social network user browsing trajectory detection based on mobile computing is completed. The implementation process is shown in Figure 4.

As shown in Figure 4, this paper first samples user behaviour characteristics, performs parameter initialisation and average mutual information entropy solution on the premise of satisfying $i = 1$, and then substitutes the solution results into the global recommendation model to determine whether the solution optimisation has been achieved. If not, return to the previous step. If it has been achieved, update the association rule feature quantity, determine whether to traverse all solution vectors, and if not, return to the average mutual information entropy solution step, If yes, the user browsing behaviour data will be de-redundant, and the de-redundant user browsing behaviour data will be output to complete the whole process of social network user browsing track detection. In the research on social network user browsing trajectory detection and promoting healthy environment construction based on soft computing, the random forest algorithm ensures that there are no false alarms and incorrect explanations through various means. Firstly, it selects the features most relevant to healthy browsing behaviour through feature selection and weight calculation, reducing the possibility of false positives. Secondly, it uses out of bag error rate to evaluate the performance of the model and identify potential false positives. Meanwhile, the random forest algorithm reduces the possibility of overfitting and further reduces false positives by limiting the number and depth of trees. Finally, due to the good interpretability of the random forest algorithm, by examining the importance of features, it is possible to understand how the model makes decisions, which can help detect and explain possible false positives. These methods collectively improve the performance and accuracy of the model, providing better support for the construction of a healthy environment for social networks.

Figure 4 Implementation flow of social network user browsing trajectory detection (see online version for colours)



So far, the mobile computing based social network user browsing path detection method has been designed. After completing the design, it is also important to evaluate whether the research on soft computing based social network user browsing trajectory detection and promoting the construction of a healthy environment has promoted the development of a healthy environment. The following are some standards that can be used for evaluation:

1 The change in user health behaviour: Observing and studying whether it leads to a change in user health behaviour is a key indicator for evaluating research effectiveness. For example, if the goal of the study is to encourage users to engage in more physical exercise, the increase in frequency and duration of user participation in physical exercise during the study period can be measured.

2 Improvement of user satisfaction and participation: Understanding user satisfaction and participation in research through survey and feedback mechanisms. If users are satisfied with the research and actively participate, it indicates that the research has a positive impact.

3 The improvement of social network health environment: Evaluating the improvement of social network health environment is also an important criterion. This includes observing whether positive and constructive communication in the network has increased, whether negative and harmful content has decreased, and whether support and mutual assistance among users have increased.

4 Improvement of data quality and effectiveness: If the purpose of the study is to improve the quality and effectiveness of the data, the effectiveness of the study can be evaluated by evaluating the quality and accuracy of the data. For example, if the use of random forest algorithm improves the accuracy of classification, then the research can be considered effective.

In summary, specific behavioural changes may include an increase in user participation in health activities, an increase in positive and constructive content on social networks, and an increase in mutual assistance and supportive behaviour among users. These behavioural changes can be observed and measured by collecting and analysing user data, in order to evaluate the promoting effect of research on the development of a healthy environment.

4 Simulation test analysis

4.1 Experimental setup

The application effect of this model is tested in MATLAB simulation environment. The processing system is win10, the CPU is Intel Core i7 3.50 GHz, the memory is 16GB and the hard disk is 2TB.

This paper verifies the proposed algorithm on two datasets. The first dataset is from the geolife project of Microsoft Research Asia. Because the real multi-source user trajectory data is difficult to obtain, this paper divides a single spatio-temporal dataset into two parts, and then regards the two parts as two social networks for identity recognition. After converting the original GPS data into dwell points, each user track is divided into two parts according to the number of dwell points. For example, if a user track contains 100 dwell points arranged in chronological order, the first 50 are divided into the first dataset and the last 50 into the second dataset. Because the sampling frequency of this dataset is high (GPS coordinates are recorded every 1 ~ 5 S or 5 ~ 10 m), it is easier to identify on it. The second dataset comes from the location-based social network brightkit. User trajectories with coordinate points less than 5 are excluded in the experiment. Like the geolife dataset, the spatiotemporal data is divided into two parts in the same way. The sampling frequency of this dataset is not as high as that of geolife, so it is relatively difficult to identify on it.

Set the sampling size of social network users' browsing trajectory data as 3,000, the size of the test dataset as 200, the number of iterations of random forest learning as 60, the similarity coefficient as 0.35, and the interference intensity of data redundancy as – 20dB. According to the above parameter settings, Li et al. (2020) and Kamal et al. (2020) mentioned in the introduction are selected as the comparison method, Test the browsing trajectory data of social network users.

Table 1 output signal-to-noise ratio of social network user browsing trajectory data De redundancy (unit: dB)

Learning times	*Paper method*	*Li et al. (2020) method*	*Kamal et al. (2020) method*
10	23.7	13.5	10.1
30	25.4	14.3	14.3
40	27.7	18.2	18.6
50	29.1	20.5	20.8

4.2 Analysis of experimental results

4.2.1 Output signal-to-noise ratio test

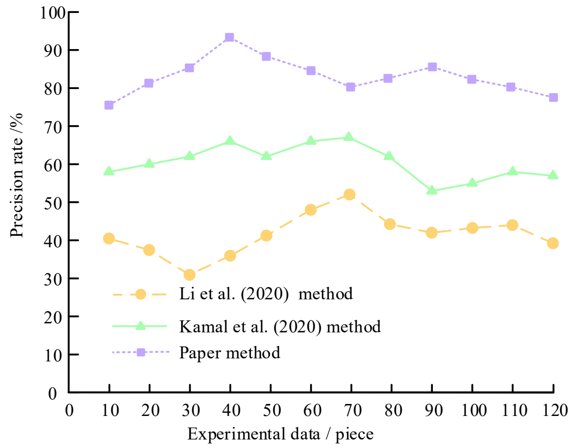
Take the output signal-to-noise ratio as the test index to test the redundancy removal effect of browsing trajectory data of social network users. The comparison results are shown in Table 1.

4.2.2 Precision and stability test

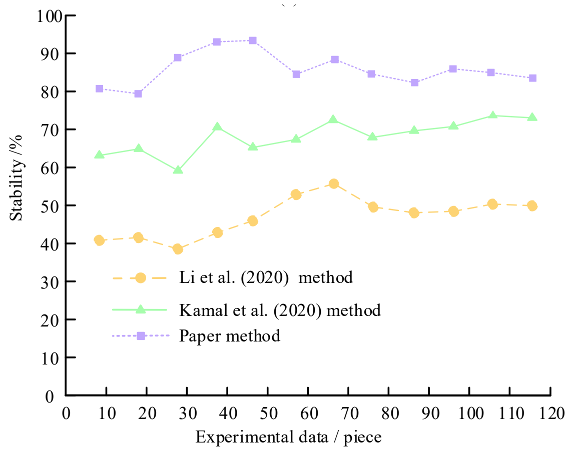
The method in this paper is experimentally compared with Li et al. (2020) method and Kamal et al. (2020) method in terms of precision and stability. The accuracy and stability comparison results of the three methods are shown in Figure 5.

As can be seen from Figure 5, because the method in this paper constructs the user behaviour feature model according to the user's browsing behaviour, and adjusts the retrieval parameters by calculating the weight of the feature item, there are other two methods in terms of information retrieval accuracy and stability.

Figure 5 (a) Comparison results of accuracy (b) Stability of three methods (see online version for colours)



(a)



(b)

5 Discussion

The above completed all the research of the experimental part, and the following conclusions can be obtained.

1 As shown in Table 1, compared with the other two methods, the output signal-to-noise ratio of the design method in this paper is better to remove redundancy, preferably 29.1 d B, while the other two methods remove less redundancy, only 20.5 dB and 20.8 dB at most. The reason for this advantage is that the method in this paper combines the matched filter detection method to achieve redundant filtering processing of the browsing track data of social network users, which can effectively remove the redundancy.

2 It can be seen from Figure 5 and Figure 6 that the accuracy and stability of the method in this paper are high, and the maximum can reach 93%. This is because the design method in this paper will build the user behaviour feature model according to the user's browsing behaviour, and adjust the retrieval parameters by calculating the weight of the feature items, so it is better than the other two methods in the accuracy and stability of information retrieval.

Based on the above analysis, it can be seen that this method can ensure the detection accuracy and stability on the basis of removing more redundancy, and has certain application value. In order to adapt to the diverse cultural backgrounds and health priorities of different regions around the world, the research on soft computing based social network user browsing trajectory detection and promoting the construction of a healthy environment can make the following summary adjustments to the system: Firstly, enhance the cultural sensitivity of the system, taking into account the languages, symbols, customs, beliefs, and health concepts of different regions. This helps to avoid cultural conflicts or misunderstandings and better meet the needs of different cultures. Secondly, customise the health needs of the system according to the health priorities of different regions. This can better meet the actual health needs of different regions and improve the practicality of the system. Once again, adjust the data collection and processing methods to adapt to the data sources, types, quality, and processing requirements of different regions. Ensure that the system can accurately and effectively collect and process data applicable to the local area. Finally, establish cooperation and partnerships with local institutions, experts, and communities to enhance the sustainability and long-term impact of research. Through cooperation and partnership, we can better understand local culture and health needs, and provide more effective solutions and improvement directions for the system. These adjustments will help improve the adaptability, effectiveness, and sustainability of the system, and better support the development of healthy environments in different regions.

6 Conclusions

In order to improve the browsing track detection and recommendation effect of social network users, this paper proposes a mobile computing based browsing track data detection method for social network users. According to the feature extraction results of social network user browsing path data, a constraint parameter model of social network user browsing path recommendation is constructed. Combined with the matched filter detection method, the redundant filtering of social network user browsing track data is realised, and the design of social network user browsing track detection method based on mobile computing is realised. The experimental results show that the output SNR of this method has a good effect of eliminating redundancy, with a maximum of 23.7 dB of redundancy removed; High accuracy and stability, up to 93%. It has better detection effect of social network users' browsing track, and has certain application value in this field. The research results of social network user browsing trajectory detection and promoting healthy environment construction based on soft computing can be applied in other social networks and contribute to the research and practice of others. This technology can provide an effective tool and method for analysing the behaviour patterns and health status of social network users, thereby supporting the promotion of a healthy environment. This is because it is a method based on soft computing, which has good generalisation performance and adaptability. It can adapt to different social network data and environments, and be customised and optimised according to specific needs.

In addition, the research results of this technology can provide useful reference and inspiration for the application of others. For example, this technology can be applied to user behaviour analysis, health monitoring, and increased user engagement in other social networks. These application areas are closely related to the theme of the study and can provide useful support and guidance for the healthy development of social networks. In summary, the research results of social network user browsing trajectory detection and promoting healthy environment construction based on soft computing can provide useful support and reference for other people's applications, and can be applied to the research of other social networks.

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