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Travel mode classification method based on travel track information

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[Abstract]

Travel pattern recognition is widely used in many aspects such as user trajectory query, user behavior prediction, interest recommendation based on user location, user privacy protection and municipal transportation planning. Because the current recognition accuracy cannot meet the application requirements, the study of travel pattern recognition is the focus of trajectory data research. With the popularization of GPS navigation technology and intelligent mobile devices, a large amount of user mobile data information can be obtained from it, and many meaningful researches can be carried out based on this information. In the current travel pattern research method, the feature extraction of trajectory is limited to the basic attributes of trajectory (speed, angle, acceleration, etc.). In this paper, permutation entropy was used as an eigenvalue of trajectory to participate in the research of trajectory classification, and also used as an attribute to measure the complexity of time series. Velocity permutation entropy and angle permutation entropy were used as characteristics of trajectory to participate in the classification of travel patterns, and the accuracy of attribute classification based on permutation entropy used in this paper reached 81.47%.

▸ **Key words**: Travel, Classification, Attribute, Extraction, Deep navigation

[요 약]

이동 패턴 인식은 사용자 궤적 질의, 사용자 행동 예측, 사용자 위치에 기초한 흥미요소 추천, 사용자 개인 정보 보호 및 지자체 교통 계획과 같은 여러 측면에서 널리 사용된다. 현재 인식 정확도는 응용 요건을 충족할 수 없기 때문에 이동 패턴 인식 연구는 궤적 데이터 연구의 초점이라 할 수 있다. GPS 내비게이션 기술과 지능형 모바일 기기의 대중화로 많은 사용자 모바일 데이터 정보를 얻을 수 있고, 이를 바탕으로 많은 의미 있는 연구가 이루어질 수 있다. 현재의 이동 패턴 연구 방법에서 궤적의 특징 추출은 궤도의 기본 속성(속도, 각도, 가속도 등)으로 제한된다. 본 논문에서 순열 엔트로피는 궤적 분류 연구에 참여하기 위한 궤적의 고유값으로 사용되었으며 시계열의 복잡성을 측정하기 위한 속성으로도 사용되었다. 속도 순열 엔트로피와 각도 순열 엔트로피가 이동 패턴 분류에 참여하기 위한 궤적의 특성으로 사용되었으며, 본 논문에서 사용된 순열 엔트로피를 기반으로 한 속성 분류의 정확도는 81.47%에 달했다.

▸ **주제어**: 여행, 분류, 특성, 추출, 딥네비게이션

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I. Introduction

With the needs of urban traffic management and the continuous development of transportation system planning, it is a key issue in the field of transportation to analyze the travel behavior of urban residents, predict the future urban travel distribution based on this, and provide basic data and evaluation reference for the division of transportation structure and transportation planning [1-6]. Urban residents' different travel modes have different impacts on urban environment, energy consumption and congestion, which to a great extent determines the composition and construction of transportation facilities of different modes in cities. Therefore, whether a city's transportation facilities are set reasonably and whether the transportation layout is effective is combined with the residents' main travel modes, which has a great impact on the travel efficiency of urban residents and the utilization of urban transportation space [7-8].

At present, the identification of travel modes is generally carried out after the estimation of traffic distribution and the division of traffic cells. The division methods mainly include lumped model and non-lumped model [9-12]. Some people have proposed to discuss the division of traffic modes by means of utility function [12-13] or neural network [14-15]. However, these methods mainly rely on a large number of travel survey data to divide travel modes from the aspects of traffic characteristics, user group characteristics or urban traffic structure characteristics. The travel combination model is established with reference to the existing mobile positioning data and communication network switching characteristics. The above methods are not applicable to the travel pattern recognition of individual travelers based on mobile phone positioning.

Literature [16] puts forward a fuzzy recognition method of travel mode based on prior knowledge. Firstly, the travel track of mobile phone users is obtained by point-to-point road matching method, and then the travel mode is judged by fuzzy recognition algorithm to determine the main travel mode of mobile phone users. However, this method simply establishes judgment rules according to the characteristics of travel modes, does not combine the transfer characteristics of travel modes, and does not distinguish between peak time and off-peak time of urban travel. It only vaguely introduces the acquisition method of mobile positioning data, and cannot judge which mobile phone positioning method is suitable for, and does not discuss the travel mode obtained by combining user travel modes.

The following terms are used in the Travel Pattern Recreation study.

Travel: Travel is the most basic concept in urban transportation planning, that is, the moving process in which urban residents use a combination of one or more modes of transportation to reach a certain destination from a certain starting point.

Travel endpoints: both ends of travel, i.e., starting point and ending point, are called travel endpoints, starting point is also called o point, and ending point is also called d point; Every trip has an o point and a d point, which constitutes an OD trip, and the d point of the last trip is often the o point of the next trip.

Stopping point: the place where the user makes a short stay in a certain trip, which is an important part of the trip. Mixed trips and trips. The mixed use of multiple vehicles in one trip is called mixed trips, in which the travel distance of each vehicle is defined as trips.

Travel mode: the combination of main travel modes adopted by residents is called the travel mode of this user.

Travel chain: residents' multiple trips connected in a period of time, in which the starting point and end point of the chain are in space. For example, the trip from home to work in the morning and the trip from the company to home in the afternoon constitute the travel chain from home to the company and then home.

Maximum utility principle: the premise for consumers to allocate and use their limited income is to maximize utility. That is to say, you can get the best return when choosing consumers. Similarly, the traveler's choice of travel mode before traveling also follows this principle.

II. Related work

2.1 Research Status of Permutation Entropy Attribute

In order to analyze the complexity of time series, many methods have been proposed, including distance-based methods, deviation-based methods and density-based methods. The new feature of trajectory analysis in this paper is the algorithm based on permutation entropy. As an attribute reflecting the complexity of time series, permutation entropy has been used in many fields.

Medical use: n. nicolaou et al. extracted the arrangement entropy features from the collected brain signals of epileptic patients and normal people, and successfully classified the healthy and sick people through the classification method of support vector machine [17-18].

Use of mechanical direction: Kochi University of Science and Technology can accurately locate the moment when shaking occurs during cutting by analyzing the noise signal of cutting metal, and find the ideal moment when cutting metal by analyzing the arrangement entropy.

2.2 Research Status of Deep Learning

In recent years, deep learning has gradually become popular in research, because it has excellent algorithm performance, and it has been paid more and more attention in academic circles. The essence of deep learning network is a kind of artificial network model.

However, there are many improvements in neural network structure and learning and training algorithms. Artificial meridian network is an algorithm in machine learning, and the development from shallow learning model to deep learning model has experienced many difficulties and problems.

(1) shallow learning.

Hinton et al. put forward a back propagation algorithm (BP) in 1980s. This BP algorithm can learn automatically in artificial neural networks to count the rules in sample data, which has certain advantages over previous operations based on manual operation through specific rules, and this has set off a new upsurge of machine learning. However, there are some problems in the training of multi-layer network because of the lack of resources and computing power of suitable labeled data. Many training models only have one layer of network, which hinders the development of artificial neural network. In 1990s, various shallow learning models of machine learning were put forward, especially SVM achieved great success in theory and application. At this time, many scholars are pessimistic about the development of deep learning, and most of them have changed their research direction, which makes deep learning enter the research trough.

(2) Deep study.

At the lowest point of neural network development in the late 1990s, several scholars believed that neural network had an ideal development prospect, including three top scholars of deep learning: Hinton, Yanlecun, Yoshuabengio. In 2006, Professor Hinton and his students published an article in the top academic journal Science, which made deep learning appear in the academic field. This paper mainly explains two points: First, the neural network with multiple hidden layers can describe the data more essentially and obtain features that are more conducive to classification; The second is to solve the problem of local optimal solution in deep learning through "initialization layer by layer". After that, the research on deep learning continued to heat up. By 2011, the error rate of speech recognition by Google and Microsoft Corporation was reduced by 20%-30%, which made a breakthrough in speech recognition. In 2012, the convolution neural network has made amazing progress in image processing, and the error rate of ILS VRC data set has been reduced from 26% to 15%. In 2015, the research of Google and Microsoft has reduced the error rate to 5%, which has surpassed the efficiency of human beings. Qin chuxiong et al. [19] have improved the training efficiency by using the deep Spirit network in a low resource training acoustic model. Xuefeng Xi et al. [20] used deep learning to conduct certain research in the direction of natural language processing.

2.3 Research Progress

Since then, in order to improve the processing speed of emergency calls in the United States, the Federal Council of the United States has required the communication network operators to achieve the positioning accuracy of the mobile phone call position before the end of the year to meet the following standards, as shown in [Table 1]:

Table 1. Requirements of the Federal Council for the accuracy of mobile phone positioning technology.

location mode	67% positioning accuracy.	95% positioning accuracy.
Handset based	<50	<150
Network based	<100	<300

The French INRETS mechanism has carried out relevant simulation experiments. After network processing, the paper analyzes the application of mobile phone positioning technology to traffic information, the possible influencing factors during collection and the corresponding collection accuracy. Under the premise of assumed positioning accuracy, the research results show that if the ratio of vehicles running on the road provides mobile phone positioning data, the error of travel time extracted on this basis is within 10%.

In order to explore the main factors affecting the accuracy and sensitivity of collecting traffic information by mobile phone positioning technology, the University of Maryland has adopted two positioning algorithms, namely hyperbola and hyperbola, and conducted relevant experiments on a long and single-lane road with different sampling time intervals, changes in vehicle position and speed, and analyzed the influences of various conditions on the accuracy and sensitivity of collecting traffic information. It has been proved that collecting traffic information by mobile phone positioning technology can judge the general characteristics of highway traffic flow.

In order to analyze the influencing factors in the application of mobile phone positioning technology, Berkeley University applied the mobile phone positioning technology according to different positioning accuracy, positioning update frequency and positioning density, and the experimental results proved the restrictive relationship between the three in positioning accuracy and sensitivity.

Italian scholars have studied the technology of traffic parameter estimation based on mobile phone positioning by means of extended Kalman filter, and the feasibility and reliability of this method have been verified in simulation experiments by establishing relevant models [21]. This paper discusses the method of extracting traffic parameters by detecting the mobile phone communication information in the vehicle, and carries out simulation experiments by using the vehicle and traffic simulator. Experiments show that the estimation errors of this method in the parameters of vehicle density, flow and speed are below 18%, 15% and 8%, respectively.

In 2000, Israeli researchers collected data on the speed and travel time of a two-lane road with a length of 10 intersections for one week by magnetic coil and mobile phone positioning method respectively. Through statistical analysis, it was found that there was a good correlation between the two methods, and it was considered that the method of traffic information collection based on mobile phone positioning could be established and applied by wireless communication solution (ATIS).

W.C. Mark Hsiao and S.K. Jason Chang tested the mobile phone positioning technology through the designed simulation experiment, and determined the positioning accuracy with long time and short sampling interval, and proved that the method can effectively obtain road traffic data.

Byeong Seok Yoo and Kyungsoo CHON put forward the calculation principle of user OD matrix on the basis of mobile phone positioning technology. After three weeks of experimental data collection, the experiments and results of mobile phone and positioning technology were compared and analyzed respectively.

Scholars such as Yasasakura and Takamasa Iryo, based on the method of mobile phone positioning, obtained and studied a large number of continuous mobile phone positioning data including time and location information, and then converted it into the mobile phone user's motion trajectory. Finally, the topological features of the road network were obtained through path matching and spatial analysis.

Scholars such as Wasan and Ratchata estimate the road traffic state by combining neural network with cell residence time, in which CDT refers to the residence time of mobile phone signal in a base station cell. They divided the road traffic conditions into three types: free, medium and crowded, and conducted relevant experiments in Bangkok, Thailand through the mobile phone software they developed. The experimental results show that the accuracy of this method in judging these three traffic conditions reaches 80%, 73.5% and 85%. Wasan et al., based on, also studied the state of road congestion with the methods of simple threshold and fuzzy logic respectively. Wasan and Kamthorn also studied the recognition of mobile phones in vehicles, and distinguished and recognized the mobile phone signals of vehicles and pedestrians in traffic by Naive Bayesian Model.

III. Classification of Travel Modes Based on Deep Neural Network

3.1 Description of Deep Neural Network Algorithm

Deep neural network has strong learning ability and generalization ability, and can get reasonable output when encountering data that does not exist in the learning process. This makes the network play an important role in finding approximate solutions of some large-scale complex problems. Neural network is nonlinear, and it can fit some nonlinear relationships well, and fit any nonlinear function in theory, but it will also cause the problem of falling into local optimal solution in the process of classification. In this paper, the deep neural network is used to classify the travel patterns of tracks, and the best classification model for travel pattern classification will be found from the experiments and the study of hidden layers and activation functions.

3.1.1 Overview of Trajectory Classification Model

The purpose of this experiment is to construct a classifier for travel pattern recognition of tracks, in which the track features used are the combination of the basic features of tracks and the arrangement entropy features of tracks, and the trip pattern classification experiment is carried out by using the composite features of tracks, and the basic steps are as follows:

(1) data preprocessing: preprocess the original GPS track data, and eliminate the track points with errors.

(2) Feature extraction of track: extract the feature value of track, extract the entropy attribute of track arrangement on the premise of track basic

features, and classify the processed data.

(3) Construct a depth neural network model to classify the trajectory data.

(4) Experiment on different activation functions and hidden layers of deep neural networks to find the best classification model.

(5) Compare the experimental results with some classical classification methods and the latest classification methods, and analyze their advantages and disadvantages.

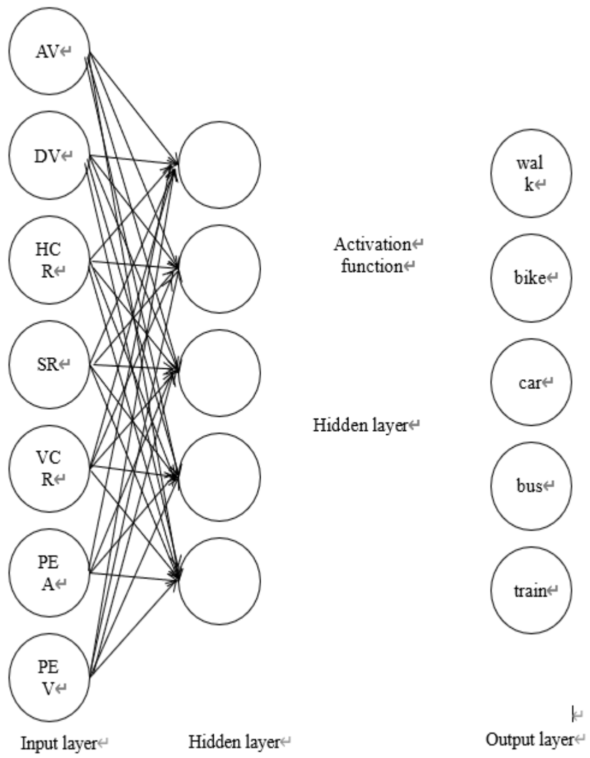

Fig. 1. Structure diagram of deep neural network for trajectory classification

3.1.2 Description of Travel Mode Algorithm Based on Deep Neural Network

(1) The processed data set is divided into training set and test set, and one track data consists of eight fields, namely, mode, speed arrangement entropy, angle arrangement entropy, average speed, speed variance, track segment direction change, pause rate and track speed change rate.

(2) There are seven eigenvalues, and the number of hidden layer nodes is set to 7. Five travel modes are classified in total. The output layer has 5 nodes.

(3) The design depth is n, and the active function is g(x).

(4) Set the iteration times as steps and the training step size as s, and use the training set Trace_trainSet to score class model training.

(5) Test the training model with the test data set trace_trainSet to verify the effect of the classification model. The flow chart of travel pattern recognition algorithm based on DNN is as follows:

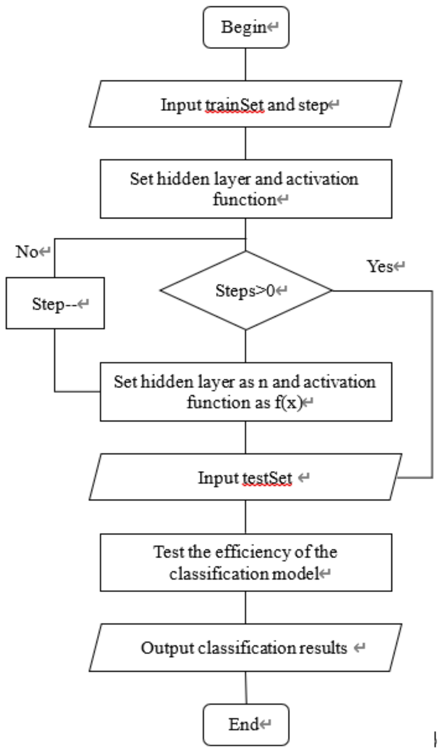

Fig. 2. The flow chart of travel pattern recognition algorithm based on DNN

IV. Experimental Results and Analysis

4.1 Experimental Analysis

In this paper, windows-based PC was used, methods in 3.1.2 was applied, a total of 18,000 tracks have been obtained through processing, and these track data are used for experiments. The data set is divided into training and test sets, in which 12,000 tracks are used as training sets and

6,000 tracks are used as test sets, and the experimental results of activation functions with different training hidden layers are compared and analyzed.

Table 2. Comparison of Experimental Results.

Test accuracy	Hide layers	Activate function
75.15%	1	ReLU
76.25%	2	ReLU
81.47%	3	ReLU
77.17%	4	ReLU
76.19%	5	ReLU
74.03%	6	ReLU
73.51%	7	ReLU
76.29%	I	Tanh
78.15%	2	Tanh
80.48%	3	Tanh
79.33%	4	Tanh
78.77%	5	Tanh
74.25%	6	Tanh
70.01%	7	Tanh
74.29%	l	Sigmoid
80.01%	2	Sigmoid
79.22%	3	Sigmoid
76.67%	4	Sigmoid
76.89%	5	Sigmoid
75.15%	6	Sigmoid
75.22%	7	Sigmoid

From the experimental results in Table 2, it can be concluded that different hidden layers and different activation functions will have certain influence on the experiment. The following two aspects are analyzed and studied.

(1) design of hidden layers.

In this experiment, different layers are used for data training, and it can be concluded that the best results can be achieved when the training layer is 3. If too many layers are used, it will not only slow down the training speed of the data model, but also cause the over-fitting problem of data training, resulting in local optimal solution and lower accuracy. From the experimental results, it can be concluded that the best hidden layer is 2 when using Sigmoid activation function at that time, and 3 when using RELU or Tanh activation function.

(2) Selection of activation function.

The activation functions used in the deep learning training model in this paper are RELU, Tanh and Sigmoid. In the experimental results, the most ideal classification result can be obtained. In the case of three hidden layers, 81.47% classification accuracy can be obtained by using RELU activation function.

4.2 Comparison between Deep Neural Network and other algorithms.

The algorithm performance comparison between deep neural network and SVM is shown in Table 3.

Table 3. Classification effect table of DNN and SVM.

Experimental method	Training time	Test time	Training accuracy	Test accuracy	Trajectory type
SVM	20.9014	1.5863	74.81%	73.16%	Walk
SVM	20.1617	0.8569	74.32%	74.44%	Bike
SVM	20.5013	1.4346	72.21%	72.55%	Bus
SVM	19.9036	0.5206	74.41%	73.20%	Car
SVM	20.1858	1.4896	76.66%	75.01%	Train
DNN	15.5553	0.5258	80.49%	80.77%	Walk
DNN	15.6781	0.1821	79.25%	79.96%	Bike
DNN	15.3352	0.5636	79.77%	79.24%	Bus
DNN	14.5841	0.2271	81.67%	80.06%	Car
DNN	15.1768	0.5894	82.15%	81.19%	Train

In the experiments in Table 3, the iterative averaging method is adopted to take values, so as to better avoid errors caused by individual experimental results. From the above results, it can be seen that the classification accuracy of the deep-warp network can reach 80%, while the classification accuracy of SVM is only about 75%. In terms of time efficiency, the training speed of the deep-warp network is 25% higher than that of the SVM classification method, and the testing efficiency is 60% higher. Therefore, it can be concluded that the deep neural network has certain feasibility and superiority in the field of traffic pattern recognition.

At present, there are some researches on trajectory classification by other classification methods, including: Naive Bayes, Bayesian Network, Decision Trees and Random Forest [22-23].

Table 4. Accuracy of different experimental methods

Trajectory category	accuracy rate
Naive Bayes	71.8%
Bayesian network,	74.9%
Decision tree,	66.9%
Random forest	75.4%

In this paper, by extracting the entropy of track feature arrangement, the classification accuracy can be improved to over 80% through the network algorithm. Compared with the classification results using only basic track attributes (speed, angle, etc.), the classification results are as follows.

With certain improvement, the deep neural network is effective and feasible in the research of track classification. Among the existing experimental classification methods, the article puts forward a travel pattern recognition method with GIS road network information. By combining with GIS road network information, the track classification effect has been further improved, and the accuracy of traffic pattern recognition has reached about 90%, among which the mode with the highest classification accuracy is bus, reaching 95%.

Table 5. Track classification based on GIS road network information

Test method	Travel mode	Accuracy rate
GIS	train	93%
GIS	bus	95%
GIS	automobile	89%
GIS	go on foot	92%
GIS	bicycle; cycling	93%
DNN	train	81.19%
DNN	bus	79.24%
DNN	automobile	80.06%
DNN	go on foot	80.77%
DNN	bicycle; cycling	79.96%

It can be seen from Table 5 of the experimental results that the accuracy of track classification based on road network information has been significantly improved, reaching more than 90%, which has exceeded the 81% accuracy of this paper.

But it needs the support of road network information and needs more cost. The accuracy of attribute classification based on permutation entropy used in this paper can reach 81.47% without the support of road network information.

Compared with the traditional classification methods, the classification accuracy of this paper has been improved to some extent, and the research results of this paper can be widely used in other areas, for example, personal mountain trips, service providers.

Transportation system has a certain value. Recommend travel modes through personal travel habits provide appropriate route planning for individuals through service providers, and provide relevant letters of travel modes for transportation systems. Information can make appropriate adjustments to the traffic system, to optimize the traffic congestion phenomenon.

V. Conclusion

With the needs of urban traffic management and the continuous development of transportation system planning, it is a key issue in the field of transportation to analyze the travel behavior of urban residents, predict the future urban travel distribution based on this, and provide basic data and evaluation reference for the division of transportation structure and transportation planning. Urban residents' different travel modes have different impacts on urban environment, energy consumption and congestion, which to a great extent determines the composition and construction of transportation facilities of different modes in the city. Therefore, whether a city's transportation facilities are set reasonably and whether the transportation layout is effectively combined with the residents' main travel modes has a great impact on the travel efficiency of urban residents and the utilization of urban transportation space.

In the aspect of classifier selection, this paper uses deep network to construct classification model. Compared with shallow model, deep neural network uses hidden multi-layer complex structure and nonlinear transformation to express high abstraction of data, which makes it easier to realize some functions of human brain. Track types can be effectively classified. Finally, based on the research of this experiment, the trajectory classification system is designed and practiced, and the research method proposed in this paper is verified. The visualization of the results verifies the effectiveness of the proposed method. This system uses Microsoft's official data set to identify track types by feature extraction of different track information and travel pattern classification, which has a good visualization effect.

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