International Journal of Engineering and Advanced Research Technology (IJEART)
ISSN: 2454-9290, Volume-3, Issue-2, February 2017

Feature Extraction of Pedestrian Behavior Propensity based on BP Neural Network

Zhenxue Liu, Yaqi Liu, Haibo Wang, Wei Tian, Xiaoyuan Wang

***Abstract*—Pedestrian is an important part of the traffic system, pedestrian travel safety, efficiency, comfort and so on have received more and more people's attention. Under the premise of the internet of pedestrians, it is of great significance to timely implement pedestrian safety warning for improving its active safety. The prerequisite for the implementation of the safety warning is to accurately identify the pedestrian's intention, and the pedestrian's intention is affected by many factors, among which the difference of the individual characteristics of the pedestrian is an important factor causing the difference of the movement intention. Thus, the reasonable pedestrian classification is of great significance to construct the scientific and reasonable pedestrian safety early warning system. Aimed at the differences of pedestrian traffic microcosmic behavior, the individual characteristics of pedestrians influencing pedestrian movement intention were analyzed thoroughly. Limited to the availability of psychological parameters of pedestrian individual differences and the external influencing factors, the concept of pedestrian behavior propensity was put forward learning from the concept of driving propensity, and it was used to describe the differences of the individual characteristics. Pedestrians were divided into three types of safety, task-based and comfortable according to the difference of actual pedestrian traffic behavior. Combined with the questionnaire survey, the non-invasive natural walking observation experiment was used to collect the movement data of three types of pedestrians. The pedestrian behavior in free flow was taken as an example, the feature vector of pedestrian behavior propensity was analyzed and extracted based on BP neural network. This study can provide theoretical support for the construction of scientific and reasonable pedestrian classification model and personalized pedestrian safety warning system.**

***Index Terms*—Behavior propensity, Feature extraction, Neural network, Pedestrian behavior.**

I. Introduction

Walking is the main transportation way of city residents' travel, and it is an indispensable way. As one of the most basic and the most ancient way to travel, the study on pedestrian traffic never stopped doing, especially with the development and prosperity of the new urbanism movement, "people-oriented" concept of city planning has become the mainstream, the need of safety, travel efficiency and comfort for traveling has been more and more higher, the study on pedestrian traffic has been paid more and more attention.

Domestic and foreign experts and scholars have done a lot of researches on pedestrian behavior in different scenarios including city roads, transport stations, large venues, and emergency evacuation, the main research method is to construct pedestrian microscopic simulation model. The main models include cellular automaton model [1-3] and mechanical model[4-10]. The common characteristics of congestion, congestion, fluctuation, transfer, phase transition and bottleneck transfer shown in macroscopic traffic flow could be basically reproduced in these models. But the fact that these phenomena are universal was not supported with enough empirical investigation, the root cause of these phenomena was not clear at present, and the underlying conditions and the mechanism of these phenomena still needs further understanding, thus the abstract modeling and parameter quantification of its essential problems are urgently needed. Based on the active safety of pedestrians, the aim is to accurately identify the movement intentions of pedestrians in complex environment, predict the danger, timely warning, reduce or avoid the occurrence of danger, and improve pedestrian safety and comfort. Efficient and accurate identification of pedestrian movement intentions is a premise for timely warning of security early warning systems. Pedestrians are affected by many factors, and the individual differences of pedestrian are important factor influencing pedestrian movement intention among them. The feature vector of pedestrian individual differences that influence the pedestrian movement intention is analyzed and extracted, the pedestrian can be classified according to this feature vector, and the more scientific and reasonable pedestrian classification criteria can be put forward. It is the core scientific problem needed to be solved to construct a personalized intention recognition model for different pedestrians through the pedestrian classification criteria. The behavior of pedestrians was observed, and non-invasive natural walking observation experiments were carried out to collect pedestrian movement data for studying the intrinsic link between pedestrian performance and individual characteristics. The pedestrians under free flow condition was taken as an example in this paper, the feature vector of the individual differences of pedestrian that influence behavior propensity was analyzed and extracted. It can be used to provide a theoretical basis for establishing scientific and reasonable pedestrian classification standard.

II. Analysis of Pedestrian Microscopic Traffic Behavior

A. Analysis of influencing factors of pedestrian behavior

Walking on the road is a kind of integrated and complex behavior. [11] Pedestrian obtained the external environment information through the perception system, the information was processed through the brain, the pros and cons of the various decisions were weighed, and then the decision

This study was supported by the State Key Laboratory of Automotive Safety and Energy under Project No.KF16232, Natural Science Foundation of Shandong Province (Grant No.ZR2014FM027, ZR2016EL19), Social Science Planning Project of Shandong Province (Grant No. 14CGLJ27), Project of Shandong Province Higher Educational Science and Technology Program (Grant No.J15LB07), and the National Natural Science Foundation of China (Grant Nos. 61074140, 61573009, 51508315, 51608313).

judgment was taken and the walking action was completed as shown in Fig.1.

The generation and development of human behavior are affected by certain objective environment. For the pedestrians, the external environment information obtained by the perception system is mainly the time-varying traffic environment information, including macroscopic traffic conditions of density, flow, velocity, blank connectivity, and the microscopic traffic conditions of the relative speed and relative distance of traffic entities. They are the external factor affecting the process of walking, they determine pedestrian behavior as external conditions, and they also influence and determine the different needs of pedestrians. Pedestrians need to avoid other traffic participants and a variety of facilities on the road during walking, and these external factors directly affect the explicit behavior of pace, stride, stride frequency and lateral oscillation, and also affect the intrinsic psychological activities of pedestrian mood, personality and attention. These psychological activities are shown through explicit behavior, such as whether give precedence to the other pedestrian traffic entities, how far to keep the distance to follow. Limited to time and effort, this article does not elaborate on this part.

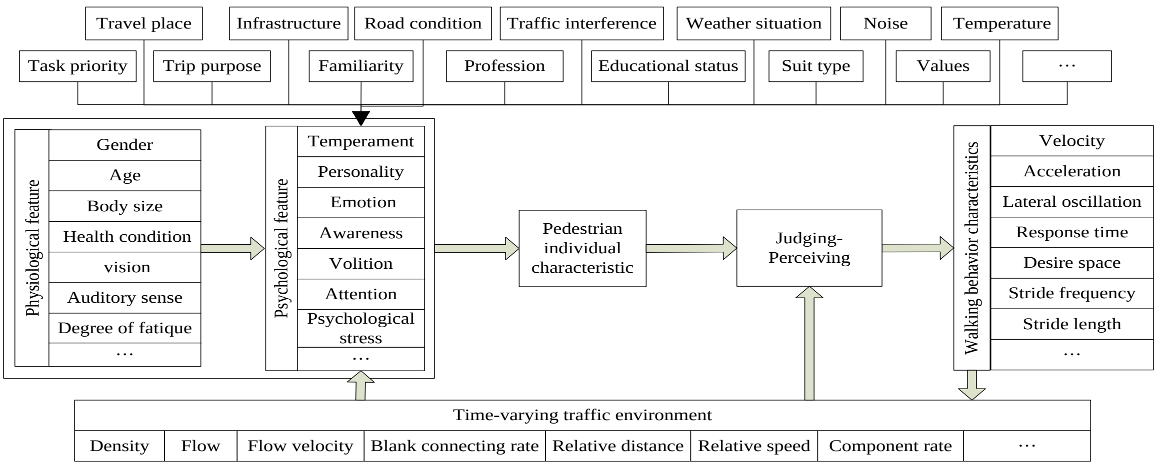

Fig. 1 Flow chart of pedestrian behavior transformation

In addition to the external environmental information, pedestrian characteristics with the heterogeneity of physical characteristics, psychological characteristics, physical characteristics and social factors are also an important factor affecting their walking behavior. For different pedestrian, the flexibility, the alertness of walking environment and the sensitivity of the environment are different, thus the intuition ability to external environment is different, the psychological state of mind will be different, and there will be different behavior even in the same environmental conditions.

B. *Pedestrian behavior propensity*

Pedestrian traffic behavior is a series of reaction actions based on the various conditions of them and surrounding environment after the pedestrian generates some travel demand. In general, pedestrian have the goal of maximizing the pedestrian traffic utility (such as: saving time, saving costs, reducing physical exertion, reducing risk, etc.). However, due to the obvious heterogeneity of physical and psychological characteristics, for different pedestrians and different traffic environment, the behaviors and the responses to the surrounding environment are different, and there are also significant differences in the selection of specific walking actions. In this paper, the concept of pedestrian behavior propensity is proposed by learning from the concept of driving propensity, [12] which is defined as the attitudes of pedestrians to objective reality traffic conditions and their corresponding decision-making propensity under the influence of various factors. It is the power system to promote the pedestrian movement, it reflects the psychological state of the pedestrians in the process of movement and it determines the pedestrian's perception of the surrounding traffic environment and the tendency of the attitude. The behavior propensity of pedestrians is divided into three types: task-based type, safety type and comfortable type. They have the following characteristics respectively:

Task-based type: This kind of pedestrians have a more urgent travel task, and they pursue a higher speed. It is possible to keep the walking speed exceeding the desired speed for a long time. Even in a more crowded environment, they may be willing to sacrifice certain walking comfortableness in order to obtain a higher speed.

Safety type: safety first, no risk, the action strategy is more conservative.

Comfortable type: This kind of pedestrians have no urgent travel tasks, no urgent need for speed, and they pursue better walking space and field conditions, they may be willing to sacrifice the speed for getting better walking space.

III. Feature Extraction of Pedestrian Behavior Propensity

Walking is a kind of way based on physical to travel, the will and action of pedestrian have synchronization, the response to the environment and their own subjective will quickly reflect in the behavior. When pedestrians walk in a free-flow environment, they will not be influenced by other traffic participants and will walk freely according to their own subjective wishes. At this time, pedestrian movement is mainly affected by factors such as gender, age, size, health status, task urgency and other characteristics of the individual factors, these factors have different degrees of influence on the psychology state of pedestrians with different behavior propensities, and these differences will express in the form of walking behavior and will ultimately reflect in pedestrian movement data. Therefore, the feature extraction method based on BP neural network in intelligent pattern recognition theory was used to analyze the measured data of pedestrian movement, and the variables with good ability to classify the propensities of walking behavior were extracted.[13] Then the behavior propensity identification model could be established based on this study.

A. Feature extraction model based on BP neural network

1) BP Learning algorithm of multi-layer feed-forward neural network

For a basic neuron model, suppose that the input is $x_i\left(i=1,2,\cdots,L\right)$, and the output is y, thus

$$net=\sum_{i=1}^{L}\omega_i x_i-\theta_i$$

$$y=f\left(net\right)$$

Where, net is the net input of the neuron, ω_i is the connection weight of the neuron and the superior neuron, $\theta_i\left(i=1,2,\cdots,L\right)$ is the threshold, and the adjustment method of the weights of the connections in the neural network is called the learning algorithm.

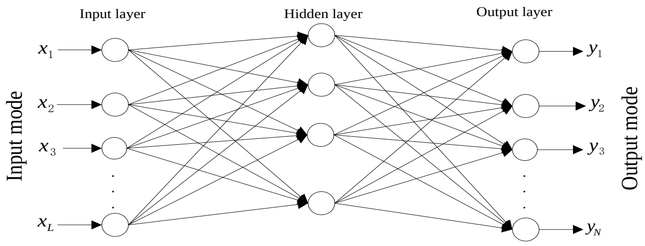

Fig. 2 Structure of multi-layer feed-forward network model

The multi-layer feed-forward neural network is the most applied for pattern recognition as shown in Fig.2. The learning process based on BP neural network (the weight adjustment process of the algorithm) is:

(a) Initialization of the weight and threshold: the initial values to all connection weights and neuron thresholds are assigned randomly;

According to the actual research object, the input $x_i\left(i=1,2,\cdots,L\right)$ and the target output $\hat{y}_k\left(k=1,2,\cdots,N\right)$ are determined.

(b) Calculate the actual output y;

$$y_k=f\left(\sum_{i=1}^{L}\omega_{ik}x_i\right) \tag{1}$$

Where, y represents the output of hidden layer or the output of output layer, ω_i is the connection weight for the network layer, $f(x)=\dfrac{1}{1-e^{-(x-\theta)}}$, and θ is the threshold for the network layer.

(c) Adjustment of the weight:

Begin with the input layer, the error signal back propagates along the connecting channel, and minimize the error through adjusting the connection weight:

$$\omega_{ik}(l+1)=\omega_{ik}(l)+\eta\delta_{pk}y_k \tag{2}$$

Where, $\omega_{ik}(l+1)$ and $\omega_{ik}(l)$ respectively are the connection weights before adjustment and before adjustment, η is the gain term and δ_{pk} is the error coefficient of node k mode p. For the p-th sample, the output error term is defined as:

$$E_p=\frac{1}{2}\sum_k(y_k-\hat{y}_k)^2 \tag{3}$$

And if k is the output layer node, then

$$\delta_{pk}=y_j(1-y_k)(\hat{y}_k-y_k) \tag{4}$$

If k is the hidden layer node, then

$$\delta_{pk}=y_k(1-y_k)\sum_k\delta_{pm}\omega_{km} \tag{5}$$

(d) If the accuracy of error or the required number of cycles is achieved, then output the result; otherwise return (b) to continue learning.

2) Feature extraction method based on BP neural network

Sensitivity was selected as the characteristic evaluation index. For the BP neural network shown in Fig. 2, the transformation function between the hidden layer and the output layer is a linear function, and the transform function between the input layer and the hidden layer adopts the S-type function, and $x_i\left(i=1,2,\cdots,L\right)$, $z_j\left(k=1,2,\cdots,M\right)$ and $y_k\left(k=1,2,\cdots,N\right)$ respectively represent the input, the output of the hidden layer and the output of the output layer, and γ_k and σ_j represent the thresholds of the hidden layer and the output layer respectively,

$$y_k=\sum_{j=1}^{M}v_{jk}z_j-\gamma_k \tag{6}$$

$$z_j=\frac{1}{1+exp\left[-\left(\sum_{i=1}^{L}\omega_{ij}x_i-\sigma_j\right)\right]} \tag{7}$$

The basis of feature selection can be obtained from the above derivation, that is, the sensitivity of the characteristic parameter x_i for the model category y_k:

$$\varsigma_{ik}=\left|\frac{\partial yk}{\partial xi}\right|\propto\left|\sum_{j=1}^{N}\omega_{ij}\upsilon_{jk}\right| \tag{8}$$

The procedure of the feature extraction algorithm based on BP neural network is shown in Fig. 3.

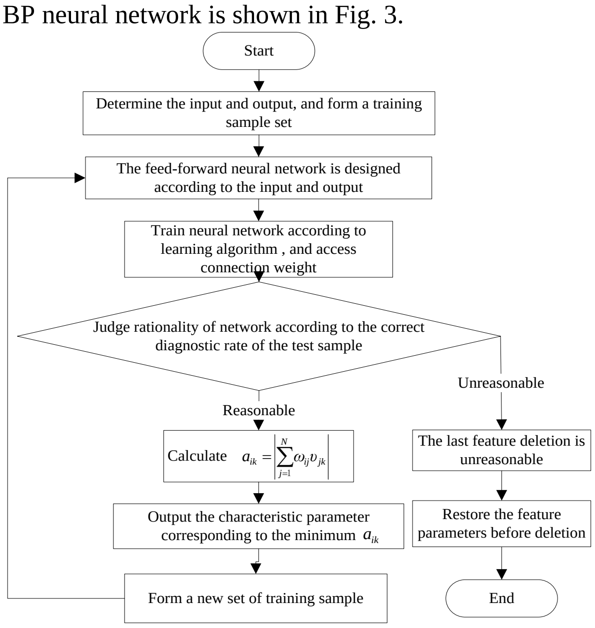

Fig. 3 Procedure of feature extraction algorithm based on BP neural network

B. Feature extraction of behavior propensity based on BP neural network

1) Experiment design

a) Questionnaire survey

According to the driver's questionnaire, the questions that can reflect the physical and psychological characteristics and behavior characteristics of pedestrians were selected to form the questionnaire as shown in Table 1, the scores of the questions were given by the incremental psychological scores according to the classical psychological scale. The greater the score, the greater the likelihood that the pedestrian belongs to the task type.

Table 1 Pedestrian psychological questionnaire

1. Your age: ____ years
2. Your profession: ____
3. Your Sex: (1) Male, (2) Female
4. Your size: (1) high and fat, (2) high and thin, (3) chunky, (4) short and thin
5. When you travel, you are generally (1) calm, (2) more calm, (3) hurried, (4) in a hurry
6. During the signal alternation, will you accelerate through the intersection? (1) never, (2) rarely, (3) sometimes, (4) often
7. When you travel, do you prefer walking at a quick pace? (1) never, (2) rarely, (3) sometimes, (4) often
8. When you travel, will you pay attention to the surrounding pedestrians? (1)must, (2) sometimes, (3) rarely, (4) never
9. When the front of pedestrians walk slowly, will you feel irritable? (1) never, (2) rarely, (3) sometimes, (4) often
10. When walking, whether you will always take beyond others into consideration? (1) never, (2) rarely, (3) sometimes, (4) often
11. When a car travel on the sidewalk, you will (1) stop and wait, (2) slow down, (3) speed up and bypass, (4)keep going with the original plan
12. When you are walking, will you follow the front of pedestrians closely? (1) never, (2) rarely, (3) sometimes, (4) often
13. When you are walking on a familiar road, will you be vigilant? (1) never, (2) rarely, (3) sometimes, (4) often
14. When you travel, will you frequent accelerate or decelerate? (1) often, (2) sometimes, (3) rarely, (4) never
15. When you walk, will you do phone calls or listen to music and other safety-neglected behavior? (1) never, (2) rare, (3) occasionally, (4) often
16. When you walk, will you glance left and right? (1) often, (2) sometimes, (3) rarely, (4) never
17. When you walk together with others, you will increase the speed unknowingly? (1) never, (2) rarely, (3) sometimes, (4) often
18. When there is a traffic congestion caused by larger crowd the front area, will you feel impatient? (1) never, (2) rarely, (3) sometimes, (4) often
19. When you can guarantee the safety of the case, whether you will avoid congestion to the motor vehicle lane? (1) never, (2) rarely, (3) sometimes, (4) often
20. When the walking space is sufficient, will you intersperse through the gap? (1) never, (2) rarely, (3) sometimes, (4) often
21. When you are waiting for a traffic signal light, will you be impatient? (1) never, (2) rarely, (3) occasionally, (4) frequently
22. In the process of travel, will you overtake her/him when the relative distance to the front walker and is narrowing? (1) never, (2) rarely, (3) occasionally, (4) frequently
23. When the walking space is enough, whether you will arbitrarily change the walking trajectory? (1) never, (2) rarely, (3) occasionally, (4) frequently
24. Once the other pedestrians overtake you, will you feel angry? (1) never, (2) rarely, (3) occasionally, (4) frequently
25. when you meet obstacles, you will (1) avoid in advance, (2) avoid normally, (3) avoid uncertainly, (4) avoid urgently

Note: 1. The number in the brackets before the option in the table are the score of the corresponding option.
2. Count the score from question 5 to 25: 21-40 is divided into comfortable type pedestrians, 41-62 is divided into safety type pedestrians, and 63-84 divided into task-based pedestrians.

200 residents in Shandong Province, Zhangdian District were asked for a questionnaire test, which including 120 men and 60 women, aged 13-69 years old. Questionnaire scores obtained by testing value were taken as sample, SPSS21.0 software was used to evaluate the homogeneity reliability and validity of the questionnaires. The internal consistency Cronbach's Alpha coefficient was $0.893 > 0.8$, and about 94% of the question score of the questionnaires were significantly correlated at significance level of 0.05 and 0.01, which indicated that the questionnaire had high homogeneity reliability and good content validity.

b) Pedestrian movement data collection experiment

Limited to the availability of the motion data recorded by the intelligent devices, the movement data of pedestrians are collected by the video method more intuitively in this paper.

(a) Experiment object

The residents in Shandong Province, Zhangdian District were taken as experiment object, 30 residents were selected as sample from each type of pedestrians and were numbered. In three types, the number of the male was 20, 16 and 14 respectively, the number of female was 10, 14 and 16, and the age distributed in the range of 17-48 years.

(b) Experiment equipment

Video method to collect pedestrian movement data on ordinary sections, the main equipment as shown in Fig. 4 included high-definition video camera, tripod, plug-in multifunction navigation recorder, notebook computer and etc.

Fig. 4 Experiment equipment

(c) Experimental content

The experiment of data collection was carried out in good weather. Zhixing Road section in Shandong University of Technology (the section length is 500 meters, the road is gentle and no roadblocks, and there are surrounding high buildings and it is easy to set up the camera) for the experimental section. It must be ensured that there are no parking and interference of other obstacles in this section during experiment process for getting more accurate data.

In order to ensure the effectiveness of experimental data and facilitate statistical analysis and processing, we limited the pedestrians that enter into the experimental section. The flow density in the experiment section was controlled to ensure less than 1.5 person/m^2 (free flow). The experimental participants were asked to pass the section with the specified direction and avoid retrograding, interruption, staying and others as far as possible. High-definition video cameras were respectively arranged in the top view and side of the experiment section, and ensured them normally work during experimental process. The whole experiment process was shot by video camera without affecting experimental participants for collecting relevant data of pedestrians.

(d) Data collection

The video tracking algorithm is used to collect the pedestrian movement data in the experiment area. The types and labels of data that can be collected are as follows:

Table2 Collected experiment data types

	Velocity	Stride frequency	Stride length	Speed change frequency	Lateral movement frequency
Label	v	s	f	w	h
Unit	m/s	time/min	m	time/min	time/min

2) Behavior propensity feature extraction process

As can be seen that the experimental data of each pedestrian fluctuates less from the experiment, which is mainly due to the less disturbance of walking in the free flow condition. Therefore, in order to simplify the process of feature extraction, prevent the neural network from over-fitting and under-fitting and ensure the balance of the samples, about 3,786 typical samples were taken as the training sample set of feature selection which were selected from a mass of experiment data. And the total numbers of samples of each type, different ages, different genders and different body size were basic equal.

Feature selection of the sample set was carried out according to the network model in Section ***III.A***. 500 samples were selected from the three types of propensities for network testing and the rest of samples were used for network training. Since the samples were obtained from the experimental data of the three types of pedestrians, (1,0,0), (0,1,0) and (0,0,1) were the definitions of the target output, and they denoted respectively three propensity types of task-based, safety and comfortable type. 5-8-3 network structure was used for network training. The connection weight between the input layer and the hidden layer was shown in Table 3, and l was the input neuron number.

Table 3 Connection weight between input layer and hidden layer

l	Connection weight between input layer and hidden layer								$\left\|\sum_{j=1}^{N}\omega_{ij}\upsilon_{jk}\right\|$
	ω_{i1}	ω_{i2}	ω_{i3}	ω_{i4}	ω_{i5}	ω_{i6}	ω_{i7}	ω_{i8}	
1	1.6379	-1.1176	0.4782	1.2034	-0.4409	-0.581	1.8503	1.4269	4.4572
2	1.2197	0.7017	-0.9817	-1.2186	0.9171	1.684	0.8108	0.6452	3.7781
3	1.7025	0.9817	1.1598	-0.03	-0.4409	1.2186	0.7075	0.9171	6.2163
4	-1.3624	1.4733	0.051	0.6314	1.0578	-1.2186	1.0544	-0.7646	0.9223
5	0.5702	1.7075	-1.4578	0.5803	0.2858	-0.4856	1.1589	0.0928	2.4521

The connection weight between the hidden layer and the output layer was shown in Table 4, and n was the output layer neuron number:

Table 4 Connection weight between hidden layer and output layer

n	Connection weight between hidden layer and output layer							
	ω_{i1}	ω_{i2}	ω_{i3}	ω_{i4}	ω_{i5}	ω_{i6}	ω_{i7}	ω_{i8}
1	0.15	0.98	1.81	-0.90	-0.00	1.00	-2.61	-1.52
2	-0.12	0.09	1.11	3.37	0.60	1.31	1.05	-0.89
3	-0.11	0.29	1.48	-0.23	-0.74	1.34	0.85	-1.99

As can be seen from the data of the last row in Table 3, the characteristic parameter that can be deleted after the first training of the network structure was the parameter of the input neuron No. 4 which corresponded to speed change frequency. After speed change frequency was deleted, the actual output can be obtained from the learning of test sample through Formula (1)-(5). A part of comparison of the actual output and the target output was shown in Table 5. It can be seen that there was no significant effect on the classification result to delete the parameter of speed change frequency, and deleting this parameter was feasible.

Table 5 Comparison of actual output and target output

Actual output	Target output	Actual output	Target output	Actual output	Target output
(0.95,0.05, 0)	(1,0,0)	(0.96,0.04, 0)	(1,0,0)	(0.93,0.07, 0)	(1,0,0)
(0,1,0)	(0,1,0)	(0.07,0.87, 0.06)	(0,1,0)	(0.08,0.92, 0)	(0,1,0)
(0,0.06, 0.94)	(0,0,1)	(0,0.16,0.84)	(0,0,1)	(0.02,0.12, 0.86)	(0,0,1)
(0.96,0.04, 0)	(1,0,0)	(0.97,0.03, 0)	(1,0,0)	(0.95,0.05, 0)	(1,0,0)
(0.02,0.04, 0.94)	(0,1,0)	(0.07,0.87, 0.06))	(0,1,0)	(0.04,0.88, 0.08)	(0,1,0)
(0,0.07, 0.93)	(0,0,1)	(0,0.16,0.84)	(0,0,1)	(0.01,0.06, 0.93)	(0,0,1)
(0.95,0.05, 0)	(1,0,0)	(0.96,0.04, 0)	(1,0,0)	(0.94,0.06, 0)	(1,0,0)
……	……	……	……	……	……

Repeated the above operation, the final choice for the propensity to distinguish pedestrian behavior was the input neuron NO.2 which corresponded to stride frequency. In the specific real-time identification model, stride frequency can be taken as the feature index of pedestrian behavioral propensity.

IV. CONCLUSION

In this paper, the movement data of three types of pedestrians (defined as task-based type, safety type and comfortable type) under free flow condition was obtained through questionnaire survey and non-invasive natural walking observation experiment. The feature extraction method based on BP neural network was used to extract feature vector with good ability to classify pedestrian behavior under free flow condition. This study will lay a foundation for the establishment of pedestrian behavior propensity identification model.

REFERENCES

[1] ictor J. Blue, Jeffrey L. Adler. "Cellular automata microsimulation for modeling bi-directional pedestrian walkways". *Transportation Research B: Methodological*, 2001, 35: 293-312.

[2] Ansgar Kirchner, Katsuhiro Nishinari, Andreas Schadschneider. "Friction effects and clogging in a cellular automaton model for pedestrian dynamics". *Physical Review E - Statistical*, Nonlinear, and Soft Matter Physics, 2003, 67(5): 056112/1-056112/10.

[3] Alizadeh R. "A dynamic cellular automaton model for evacuation process with obstacles". *Safety Science*, 2011, 49(2): 315–323.

[4] Matsushita Satoshi, Okazaki Shigeyuki. "A study of Simulation Model for Way Finding Behavior by Experiments in Mazes". *Journal*

of Architecture, Planning, Environment Engineering, 1991, 429: 51-59.
[5] Dirk Helbing, Peter Molnar. “Social force model for pedestrian dynamics”. *Physical Review E*, 1995, 51(5): 4282-4286.
[6] Dirk Helbing, Illes Farkas, Tamas Viscsek. “Simulating dynamical features of escape panic”. *Nature*, 2000, 407(28): 487-490.
[7] Lakoba Taras I, Kaup D J, Finkelstein Neal M. “Modifications of the Helbing- Molnar- Farkas- Vicsek social force model for pedestrian evolution”. *Simulation*, 2005,81(5): 339-352.
[8] Daniel R Parisi, Marcelo Gilman, Herman Moldovan. “A modification of the social force model can reproduce experimental data of pedestrian flows in normal conditions”. *Physica A: Statistical Mechanics and its Applications*, 2009,388(17): 3600-3608.
[9] D Helbing, A Hennecke, V Shvetsov, and M. Treiber. Micro-and macro-simulation of freeway traffic [J]. Mathematical and Computer Modelling, 2002, 35(5-6), 517-547.
[10] Robert Kukla, Jon Kerridge, Alex Willis and Julian Hine. “PEDFLOW: Development of an Autonomous Agent Model of Pedestrian Flow”. *Transportation Research Record*, USA, 2001, 1774, 11-17.
[11] Dewei Li, Baoming Han. Pedestrian traffic. Beijing. China Communication Press, 2011.
[12] Xiaoyuan Wang, Jin Liu, Jinglei Zhang. “Dynamic recognition model of driver’s propensity under multilane traffic environments”. *Discrete Dynamics in Nature and Society*, 2012.
[13] Xiaoyuan Wang, Jinglei Zhang, Xuegang(Jeff) Ban, Derong Tan. “Dynamic Feature Extraction Method of Driver’s Propensity under Complicated Vehicle Group”. *Advances in Mechanical Engineering*, 2013,1-10.

Zhenxue Liu
She was born on 16th July, 1991 in Shandong province, China. She is currently working toward the M.S. degree in traffic and transportation engineering. Her research interest include analysis of pedestrian behavior, controlling and cooperative intelligence of human-vehicle-environment.

Yaqi Liu
He was born on 12th December, 1989 in Shandong province, China. He is currently working toward the M.S. degree in traffic and transportation engineering. His research interests include analysis of driving behavior, affective computing, controlling and cooperative intelligence of human-vehicle-environment.

Haibo Wang
He was born on 13th September, 1990 in Shandong province, China. He is currently working toward the M.S. degree in traffic and transportation engineering. His research interests include analysis of cyclist behavior, controlling and cooperative intelligence of human-vehicle-environment.

Wei Tian
He was born on 26th January, 1991 in Shanxi province, China. He is a graduate student at the Shandong University of Technology, and major in transportation engineering. His research interests include Urban Transportation Planning, smart city, Intelligent Transportation.

Xiaoyuan Wang
He was born on November, 1970 in Shandong province, China. He works as a professor with the School of Transportation and Vehicle Engineering, Shandong University of Technology. He also served as a visiting research fellow in State Key Laboratory of Automotive Safety and Energy, Tsinghua University. He is specialized in intelligent transportation systems, especially in cooperative intelligence of human-vehicle-environment. He has authored or coauthored more than 100 publications in international journals.