Comprehensive Evaluation Method of Driving Behavior Based on Neural Network

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Abstract. In recent years, the number of traffic accidents in the world has increased sharply. Reasonable mining of the OBD data generated in the process of vehicle driving will help to improve traffic safety. However, the existing driving behavior scoring models have the following shortcomings: the indexes are not comprehensive enough, and the selection of weights is not objective. In order to solve these shortcomings, this paper proposes 16 driving behavior indexes and related definitions; the neural network is used to construct the model to distribute the weight reasonably; a new comprehensive evaluation model of driving behavior is constructed. The feasibility and efficiency of the model are verified by experiments on real vehicle OBD data sets.

1. Introduction

According to the data of the World Health Organization, the number of car accidents in the world has increased sharply in recent years. In order to improve the situation of the rapid increase in the number of traffic accidents, under the background of the rapid development of Internet of Vehicles technology, it has become an urgent need to deeply mine the vehicle driving information. Nowadays, the comprehensive scoring method of vehicle driving behavior is mainly carried out from the following perspectives. Chantranuwathana S conducted a comprehensive evaluation of driving fuel consumption by calculating the average speed of the car and making interval analysis [1]. This method is very simple to calculate, and the overall fuel consumption score can be obtained only by the average speed of the car, but the accuracy is not high; By designing dangerous driving detection algorithms, Literature [2] calculated the subtractive items in the score and finally sums up with the fuel consumption score to obtain the comprehensive score of driving behavior. This method has the advantages of simple structure and convenient operation. It only needs to deal with the deduction items in the indexes to get the final driving behavior score, but the selected indexes are insufficient, and the subjectivity is strong in the weight setting; Li C constructed the freeway evaluation index system, and completed the comprehensive evaluation of the freeway by using the BP neural network to build a model [3]. This method can accurately and effectively calculate the evaluation grade of
expressway, but the structure of the model is complex, the efficiency is low, and the interpretability is poor; Lopez JR modelled the driving scoring calculation task as a regression problem, and proposed a new scoring function, which is generated by a heuristic automatic program called genetic programming (GP). Finally, the driving behavior score is delivered to the automotive intelligent device [4]. The calculation effect of this method completely depends on the historical data. Once there is deviation in the historical data or there are few sample data, the accuracy of the model will be affected.

Therefore, in the quantitative calculation model of driving behavior, there are mainly the following problems: the factors considered in the quantification of the driving score are not comprehensive enough, and the calculation characteristics of the score model do not conform to the actual situation. In this case, this paper combines neural networks and comprehensive evaluation methods to propose a multi-faceted driving behavior evaluation model.

2. Related work

Back propagation (BP) neural network [5] is a concept proposed by scientists Rumelhart and McClelland in 1986. It is a multi-layer feedforward neural network trained by error back propagation algorithm. Among neural networks, BP neural network is the most widely used.

The BP neural network algorithm includes two processes: the forward propagation of the signal and the backward propagation of the error. It calculates the error output according to the direction from input to output, and adjusts the weight and threshold from output to input [6]. After repeated learning and training, the training stops when the network parameter corresponding to the smallest error is found. At this time, the trained neural network can process the non-linearly transformed information with the smallest output error on the input information of similar samples [7].

BP neural network essentially completes a mapping function from input to output, and mathematical theory has proved that it has the function of completing any complex nonlinear mapping task. This makes it particularly suitable for solving problems with complex internal mechanisms [8].

3. Index system

By combining OBD data and weather data, this paper selects 16 driving behavior indexes and proposes corresponding definitions for the calculation of these indexes. These indexes can strictly correspond to the three influencing factors of safety, efficiency and energy consumption.

Calculating each index separately will provide data support for the subsequent driving behavior scoring model. Table 1 shows the details of these 16 indexes.

| Driving behavior indexes | Index type | Description |
|--------------------------|------------|-------------|
| The times of rapid acceleration | Safety | Excessive acceleration |
| The times of rapid deceleration | Safety | Excessive reverse acceleration |
| The times of fatigue driving | Safety | Driving for a long time |
| The times of idle preheating | Safety | The car hasn't moved for a long time after starting |
| The times of coasting with engine off | Safety | The car go on after the flameout |
| The times of speeding | Safety | The speed is too high |
| The times of sharp turning | Safety | Turning angle is too large during high-speed driving |
| Whether the car is within the scrapped mileage | Safety | The car exceeds the safety mileage |
| The average speed while driving | Efficiency | Average speed |
| Speed stability | Efficiency | Driving speed stability |
| The time of exceeding the speed limit in case of low visibility | Safety | Driving at high speed in low visibility |
| The time of high-speed driving in case of side | Safety | Driving at high speed when there |
4. Driving behavior evaluation model

By combining BP neural network and comprehensive evaluation method, and according to the characteristics of safety, efficiency and energy consumption, this paper puts forward the following calculation model.

\[
S_D(a) = (1 + \exp(-\sum_{i=1}^{n} (y_i(a) \times p_i) - \theta)))^{-1}
\]  

(1)

Where \( S_D(a) \) is the comprehensive score of vehicle \( a \), \( y_i(a) \) is the \( i \)-th index value of vehicle \( a \), \( p_i \) is the weight of the \( i \)-th index, and \( \theta \) is the threshold parameter of neural network output layer. Both \( p_i \) and \( \theta \) depend on the network model to select according to the data set.

5. Algorithm analysis and implementation

5.1. Technical roadmap

After data integration of vehicle OBD data and weather data; null value deletion, deduplication, outlier correction, and data format unification are completed; driving behavior mining is performed to obtain three types of indexes: safety, efficiency and energy consumption; the training set is passed into the neural network to complete the automatic selection of weights; the score of driving behavior is calculated by the network model; finally, the results are visualized.

5.2. Parameter settings

1) In the model, \( p_i \) is the weight of the \( i \)-th index, the importance can be intuitively reflected through these weights. In the existing quantitative model, the weight is mainly obtained by manual selection,
statistical method and analytic hierarchy process, but these methods cannot effectively give reasonable and accurate weights to solve the practical problems. In this paper, the back propagation neural network is used to construct the nonlinear model, and the above 16 weights are automatically selected by the network model based on the historical data set.

2) In the network structure, 16 input neurons and one output neuron can be determined according to the input and output; through cyclic training verification, it is determined that the maximum training times is 15000, and the minimum error of the training target and the learning rate are both 0.1; the number of hidden layer is determined according to the empirical formula \( n_2=2n_1+1 \) [9], where \( n_2 \) is the number of hidden layer neurons and \( n_1 \) is the number of input layer neurons, thus 33 hidden layer neurons can be set.

6. Experiment and result analysis

6.1. Experimental environment

The experimental platform selected for this experiment is Pycharm 2019.1.3 x64+Python3.6; the operating system is Win10 Professional 64-bit; the processor is Intel(R) Core(TM)i5-6500 CPU @3.20GHz; the memory bank capacity is 20.0GB.

6.2. Data source and preprocessing

In order to reflect the superiority of the proposed model more objectively, this paper conducts experiments on 449 real truck OBD data.

Obtained OBD data usually has problems such as irregular format, redundant data, missing part of information, etc. In order to ensure the authenticity and reliability of the experimental results, format conversion, redundant field deletion, and experimental data storage must be completed.

6.3. Experimental results and analysis

The training set is constructed by expert evaluation, then the model is trained and the comprehensive score of driving behavior is calculated. The scoring results are obtained, some data are shown as follows.

| Vehicleplate number | Rapid times | Deceleration times | FatigueDriving times | IdlePreheating times | Diseconom Speed rate | Total score |
|---------------------|-------------|--------------------|----------------------|----------------------|----------------------|-------------|
| AB00365             | 91          | 94                 | 0                    | 2                    | 0.476636             | 78.69113    |
| AB00370             | 98          | 110                | 0                    | 1                    | 0.999777             | 73.55906    |
| AB00380             | 110         | 102                | 0                    | 0                    | 1                    | 74.04497    |
| AB00386             | 157         | 164                | 3                    | 6                    | 0.779366             | 33.49892    |
| AD00038             | 301         | 309                | 0                    | 7                    | 0.711921             | 68.70123    |
| AD00040             | 231         | 240                | 0                    | 0                    | 0.857497             | 68.83804    |
| AD00101             | 302         | 361                | 1                    | 7                    | 0.974178             | 63.0514     |
| AD00104             | 284         | 314                | 2                    | 0                    | 0.958486             | 62.73623    |

The driving behavior of 449 vehicles is imported into the scoring model, and the summary of the scores of all drivers is shown in the figure below.
It is found that the scores roughly conform to the negatively skewed distribution, and most of the drivers' scores are concentrated in the interval [60,80]. There is only one vehicle in the range [85,90], but the scores of two vehicles are in the range [20,25], and one vehicle is in the range [25,30].

In order to verify the final scores of the six vehicles with the lowest scores, we analyze their behavior statistics, as shown in the following table.

Table 3. Six lowest-rated driving behaviors

| Vehicle plate number | Rapid times | Deceleration times | Fatigue Driving times | Speeding times | Average speed | Diseconomic Speed rate | Total score |
|----------------------|-------------|--------------------|-----------------------|----------------|---------------|------------------------|-------------|
| AD00050              | 252         | 255                | 5                     | 549            | ...           | 76.43174               | 0.624188    | 20.3271 |
| AD00292              | 289         | 295                | 4                     | 501            | ...           | 69.84067               | 0.711437    | 21.28982 |
| AD00320              | 96          | 93                 | 0                     | 458            | ...           | 77.23121               | 0.730658    | 25.99487 |
| AD00369              | 81          | 80                 | 0                     | 367            | ...           | 77.67321               | 0.901801    | 33.17816 |
| AB00386              | 157         | 164                | 3                     | 319            | ...           | 70.03252               | 0.779366    | 33.49892 |
| AD00290              | 36          | 35                 | 0                     | 361            | ...           | 51.69119               | 0.963675    | 34.71924 |

It is not difficult to find that the drivers of these vehicles have a lot of speeding behaviors, and some of them have many dangerous behaviors of fatigue driving. The results also verify the rationality of the model in one aspect.

7. Conclusion

Nowadays, The Internet of Vehicles is becoming more and more mature. This paper deeply mines and analyzes the OBD data of 449 real transport vehicles combined with weather data. This paper puts forward the judgment criteria of 16 driving behavior indexes, and corresponds them to three types: safety, efficiency and energy consumption. In the construction of the evaluation model, this paper uses the weighted method to construct the model, and transforms the problem into the problem of weight selection. This paper selects BP neural network to calculate the weight. In the experiment, the expert score results were used as training samples to train and learn the model, demonstrating the feasibility of the model. In addition, this paper summarizes the scores of all vehicles, finds out the specific reasons for low-scoring vehicles, and provides a reference for drivers and business management departments from another perspective.

Acknowledgments

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