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Abstract

In order to detect the state of vehicle trajectory, an abnormal prediction method of vehicle trajectory based on bionic neural network, called ADFA-LSTM, is proposed according to the temporal characteristics and position relationship of vehicle trajectory. The long-short memory neural network (LSTM) is used to predict the trajectory in the short term based on the characteristics of the vehicle's historical trajectory, and the trajectory prediction results are analyzed to identify the abnormal trajectory. In the process of trajectory prediction, the improved biomimetic firefly algorithm (FA) is used to optimize the prediction the parameters of LSTM model, which improves its processing efficiency and enhances its fitting ability. Through a lot of experimental analysis, the detection effect of the algorithm is verified.

Keywords (separated by '-')

Trajectory - LSTM - Firefly algorithm - Anomaly detection

ADFA-LSTM: An Abnormal Trajectory Prediction Method Based on Bionic Neural Network

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Abstract. In order to detect the state of vehicle trajectory, an abnormal prediction method of vehicle trajectory based on bionic neural network, called ADFA-LSTM, is proposed according to the temporal characteristics and position relationship of vehicle trajectory. The long-short memory neural network (LSTM) is used to predict the trajectory in the short term based on the characteristics of the vehicle's historical trajectory, and the trajectory prediction results are analyzed to identify the abnormal trajectory. In the process of trajectory prediction, the improved biomimetic firefly algorithm (FA) is used to optimize the prediction the parameters of LSTM model, which improves its processing efficiency and enhances its fitting ability. Through a lot of experimental analysis, the detection effect of the algorithm is verified.

Keywords: Trajectory · LSTM · Firefly algorithm · Anomaly detection

1 Introduction

With the development of Global Positioning System (GPS), wireless technology and location-aware services, a large amount of trajectory data has now been collected. In the field of data mining of moving objects, the problem of trajectory anomaly detection is a hot topic [1]. How to dig out the behaviors and factors related to road traffic safety, and give warnings to the safety behavior of vehicles, so as to effectively reduce traffic violations and reduce the incidence of accidents, has become an urgent problem in the process of modern transportation [2]. According to the driving data of road vehicles, the abnormal identification of the vehicle trajectory is carried out, and the establishment of a driving safety monitoring model can more comprehensively and accurately detect and predict the dangerous state that may cause a traffic accident, and provide a valuable reference for vehicle safety warning. Therefore, in-depth research on driving safety monitoring technology has important significance and use value.

In this paper, we mainly analyze the trajectory data through the bionic deep learning model, identify the abnormal trajectory of the vehicle, and evaluate the driving safety level of the vehicle. The contributions of the paper are summarized as follows. (1)

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The neural network structure of LSTM model is optimized by the brightest individual disturbance adaptive firefly algorithm (ADFA), and the vehicle trajectory prediction model is established based on it. (2) The trajectory prediction results are analyzed in combination with the trajectory characteristics, and the abnormal trajectory evaluation index is given to judge the situation of vehicle trajectory to identify abnormal trajectories.

2 Related Work

Anomaly detection of traffic trajectory is a hot research topic. Traditional mathematical model and machine learning model are two important methods for anomaly detection of traffic trajectory.

Among them, the traditional mathematical model mostly adopts statistical probability method, and its core idea is multi-detection fusion strategy, which comprehensively judges different motion trajectories, usually including Hidden Markov Statistical Model (HMM), Bayesian decision probability model and Linear regression and function approximation model [3–5]. Zhang et al. measures the similarity between trajectories by calculating the relative similarity, and then uses the Gaussian model to match the new trajectory data to detect whether the trajectory is abnormal or not [6]. However, the correlation between trajectories is not considered, so the efficiency of abnormal detection is not high. Pang et al. adopts a Bayesian deep learning method to effectively predict the trajectory [7]. Due to the difference of features of trajectories, Venkatesan considers the global features of trajectories, including direction, speed and distance. The abnormal trajectories are found by measuring the distance difference, speed change and direction correlation between trajectory points [8]. But the method ignores the local difference between trajectories. Wonjik et al. uses a path prediction method of self-organizing incremental neural network for possible errors, and evaluates the errors effectively [9–11].

Machine learning model has the advantages of fast processing speed and strong learning ability, and it's applicable in processing nonlinear mapping data such as traffic trajectory [12, 13]. Kong etc. comprehensively considers factors such as longitude, latitude and vehicle route, uses the particle swarm optimization algorithm to optimize parameters of support vector machine, and predicts vehicle speed based on this model, and gives regional congestion level [14]. Sovan et al. extracts some features of trajectory points under different tags, and then detects abnormal trajectories in real-time trajectories data [15]. Debat uses a neural network with peak-time-related plasticity rules to train in a supervised manner to predict trajectories [16]. However, these methods simply consider the characteristics of trajectory points, without considering the continuity of trajectory sequence, so the effect is limited. De et al. decompose GPS data into multiple indefinite trajectory sequences, and uses the time series learning ability of B-RNN neural network to identify the overall characteristics of historical trajectory, and the detection effect is better [17].

According to the above-mentioned trajectory anomaly detection work, the current research on trajectory prediction and anomaly detection mainly focuses on the research on trajectory prediction methods, often using empirical value to select feature parameters and forcibly truncate long trajectories, less considering the impact of trajectory factors on the model, such as the problem of factor selection and the problem of variable length trajectory sequence, which have a great impact on the accuracy of model prediction. Therefore, this paper proposes a bionic neural network model based on trajectory timing features. Firstly, the influence degree of each attribute of trajectory on the model is analyzed. Secondly, the embedding layer is used to complete and align the timing trajectory sequence, and then the vehicle trajectory information is predicted by the improved LSTM model. Finally, the anomaly analysis of trajectory data is completed.

3 Trajectory Prediction Analysis Based on ADFA-LSTM

3.1 Definitions

The collection of a series of points formed by moving objects in space motion is called spatial-temporal trajectory, which generally includes longitude and latitude, time, direction, speed, etc. Based on the features of spatio-temporal trajectory, this paper gives the following definitions.

Definition 1 Trajectory (T): The spatio-temporal trajectory sequence T is a set of points with some information such as time stamps and positions, that is, T $= <p_1, p_2, ..., p_i, ...p_n>$. T represents a sequence of trajectory points formed by a vehicle and contains n trajectory points.

Definition 2 Trajectory point (P$_i$): The point P_i is a position in the trajectory, typically $P_i = <x_i, y_i, \mathrm{s}_i, h_i, t_i>$ $(i = 1, 2, 3, \cdots, m)$, x_i, y_i is the spatial coordinate (longitude and latitude), v_i is the speed of P_i, h_i is the height of P_i, t_i is the timestamp.

Definition 3 Trajectory length (T.length): The length of a trajectory refers to the number of trajectory points contained in a trajectory sequence from the start point to the end point.

3.2 Trajectory Prediction Model Based on LSTM

As a variant of RNN neural network, LSTM solves the defect of its long-term dependence by adding four interaction layers, which can perform better in longer time series and has great advantages in processing traffic trajectory. Therefore, this paper selects LSTM model for vehicle trajectory prediction.

Figure 1 shows the trajectory prediction model based on LSTM established in this paper, mainly including four layers of structure: input layer, embedded layer, hidden layer and output layer.

(1) Input layer. The input layer is the input sequence of LSTM network, and the transmitted data is the original vehicle trajectory data collected through GPS. Each trajectory data represents a travel path of a vehicle, which is composed of n $(0 < n \leq T.length_{\max})$ trajectory points, in which each trajectory point contains timestamp, longitude, latitude, height, speed and so on. Each trajectory has different length, so it needs to be aligned.

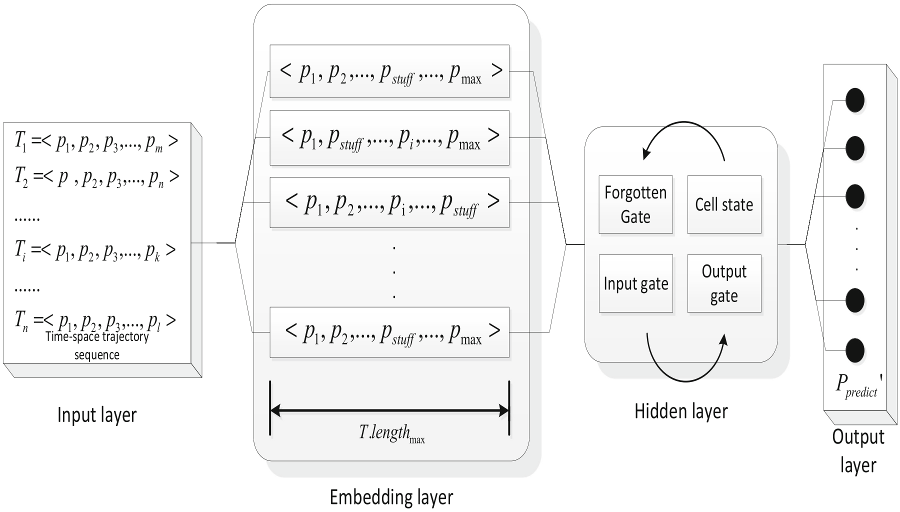


Fig. 1. LSTM trajectory prediction model

(2) Embedded layer. This layer transforms high-dimensional sparse data into low-dimensional dense vectors. In this paper, the embedded layer is used to convert the discrete data of the input layer into a vector with fixed size to solve the input problem of variable length sequence of LSTM model. For LSTM model, the variable-length trajectory cannot be directly trained, so it is necessary to combine the embedding layer to vectorize the trajectory data and convert it into a fixed-length trajectory sequence.

(3) Hidden layer. The training and learning of LSTM for trajectory sequence is mainly carried out in the hidden layer, and the structure includes input gate, output gate, forget gate and cell state.

(4) Output layer. The output layer obtains the position point prediction sequence by processing the data generated by the hidden layer.

In general, the calculation process of LSTM prediction model in this paper can be summarized as follows: combined with the historical trajectory input and current trajectory, the useful information for subsequent trajectory can be transmitted through forgetting and memorizing new information in cell state, while the useless information is discarded.

3.3 Improved Firefly Algorithm Optimizing LSTM Neural Network

Aiming at the defects of slow convergence speed and complex parameter adjustment process in the training of LSTM model, this paper optimizes the network structure by firefly algorithm (FA) to improve the prediction performance. Because the firefly algorithm itself also has the problems of easy falling into local optimization and easy oscillation, this paper establishes an adaptive FA algorithm based on the brightest individual disturbance (ADFA). The improvement of ADFA for FA algorithm mainly includes two aspects:

a) Introduce the update strategy of the brightest individual perturbation position based on the diversity of the population, and enlarge the global search range of the firefly algorithm to prevent falling into the local optimum. Since all fireflies will look for the brightest individual to move in each iteration, the brightest individual will not be updated before the brighter individual appears. Therefore, a disturbance mechanism is added to the brightest individual to actively seek a position with a higher fitness value.

b) Using an adaptive function, the step factor is adaptively changed with the number of iterations, so that the algorithm pays more attention to the global search in the early stage, and pays more attention to the local search in the later stage to solve the problem of continuous oscillation near the optimal solution in the later stage of the search.

Its core processes for LSTM parameter optimization include:

Step 1: Initialize algorithm parameters, including the firefly population size P, problem dimension N, maximum attraction β, individual disturbance factor S, light intensity absorption coefficient γ, initial step factor α, maximum iteration number max and search accuracy W;
Step 2: Initialize that individual position of the population, and calculate the individual brightness of the firefly through the objective function;
Step 3: Determine the individual moves in a brighter direction through the brightness difference between the fireflies and the attractiveness value β;
Step 4: Update the position according to the individual disturbance factor S;
Step 5: Recalculate the brightness of the fireflies according to the differences in the positions of the updated individuals;
Step 6: If the maximum number of iterations max is reached or the search accuracy W is satisfied, go to step 7; otherwise, continue iteration, use the adaptive function to determine the step size, go to step 3, and start the next search;
Step 7: Output the optimal firefly individual set, that is, the LSTM optimal parameter set.

3.4 ADFA-LSTM Trajectory Prediction Algorithm

Because GPS trajectory data has the characteristics of time and position information before and after, the LSTM neural network model has more advantages than other neural network algorithms, but it still has problems such as slower parameter search and easy fall into local optimality. Therefore, in our paper, ADFA algorithm is used to optimize its parameters, and then the vehicle historical trajectory data is used as input for training to establish a vehicle trajectory prediction model. The model framework of the algorithm is shown in Fig. 2.

The model mainly includes three stages: the first stage mainly selects feature attributes and sequence optimization on the historical trajectory of the vehicle; the second stage optimizes the LSTM model parameters through the ADFA algorithm, and determines the LSTM optimal parameter set based on the brightest individual firefly iterative optimization; in the final stage, train the LSTM model according to the historical trajectory to predict the position at the next moment, and add the predicted data to the data set for continuous position prediction to obtain the final prediction result. According to the above process, the algorithm is described as follows (Table 1):

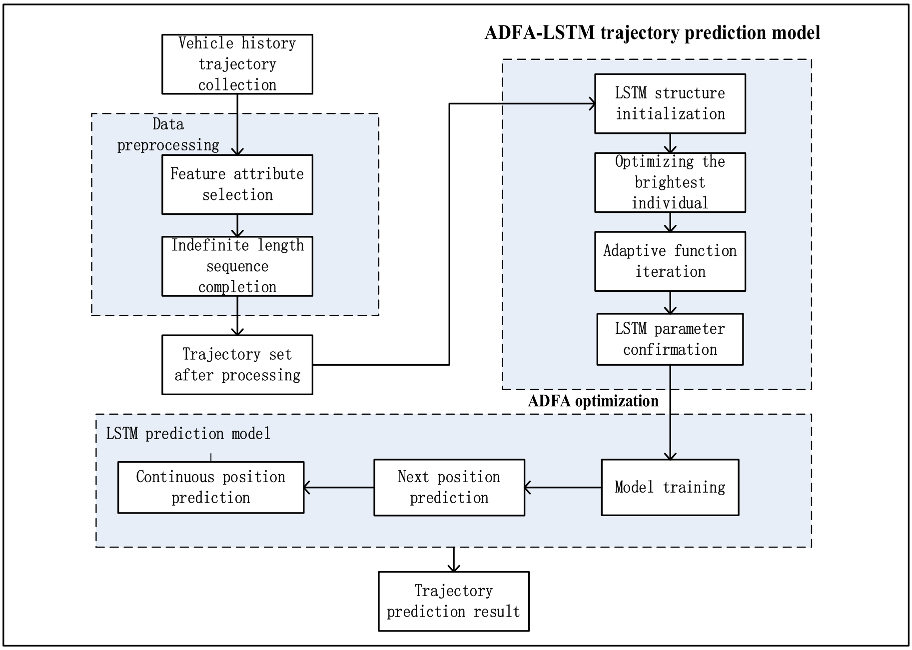


Fig. 2. ADFA-LSTM model frame diagram

Firstly, the trajectory sequence Traj_i is aligned through the embedding interface, and then the preprocessed trajectory sequence is divided into a training set and target set, which are input into LSTM neural network for training. The ADFA algorithm is used to optimize the training parameters. Firstly, find NewBest () is used to implement the brightest individual disturbance location update strategy, and then the FitnessSelf-Function() is used to recalculate the fitness value of the firefly to speed up the location update process until the iteration conditions are met, and the LSTM optimal parameter set is obtained. Finally, the historical trajectory sequence to be predicted is input into the optimized LSTM model to obtain the final trajectory prediction result.

Table 1. Trajectory prediction algorithm based on ADFA-LSTM

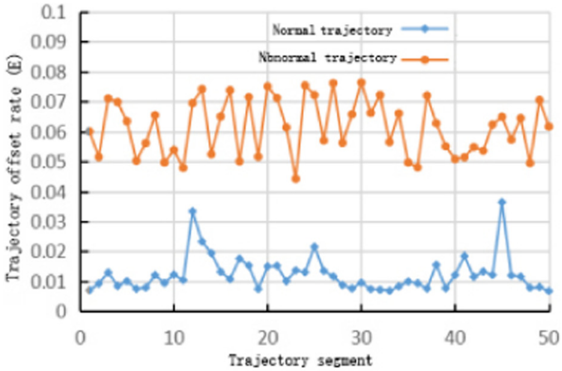
Algorithm 3.1 Trajectory Prediction Algorithm Based on ADFA-LSTM
Input: vehicle trajectory sequence set $Traj_{SA}$
Output: Future vehicle location $P_{prediction}$
1. for each $\mathrm{Traj}_i \in Traj_{SA}$ do
2. $\mathrm{Traj}_i = embedding(Traj_i)$ // Time series data completion
3. for (k in st: N)
4. $\mathrm{DataSet\ trainSet} = \mathrm{Traj}_i.subTraj(0, k-1)$; // Sliding window dynamic training
5. $\mathrm{DataSet\ targetSet} = \mathrm{Traj}_i.subTraj(k-1, k)$;
6. LSTM.train (trainSet,targetSet);
7. FA.train ()← LSTM.train ();//LSTM parameter optimization
8. While (t < MaxGeneration)
9. FA.best ()← FindNewBest (); // The brightest individual perturbation optimization
10. FA.update ()← FitnessSelfFunction (); // fast iteration of adaptive function
11. LSTM.train ()←FA.best ();
12. end for
13. end for
14. DataSet paramSet = embedding ($T_{current}$);
15. $P_{prediction}$= LSTM.learn (paramSet);

3.5 Abnormal Trajectory Detection

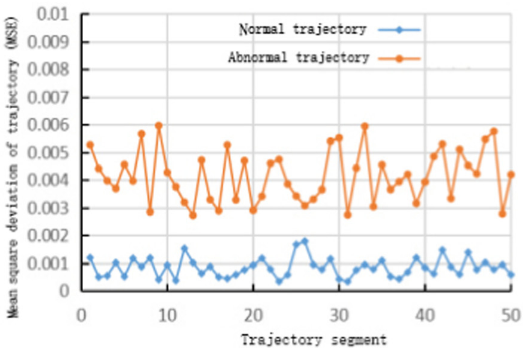
After the trajectory prediction model is used to obtain the prediction information of the trajectory, the trajectory features are then extracted to analyze the trajectory prediction results, and the abnormal conditions in the trajectory can be judged by detecting the difference between the normal and frequent trajectory. The specific detection ideas are as follows:

(1) Based on the ADFA-LSTM trajectory prediction model, extract the key features of the trajectory to be measured, and establish anomaly detection classification labels based on the trajectory data and road features.
(2) Based on the trajectory characteristic, the anomaly evaluation index is established, and the detection threshold of the evaluation index is set by analyzing the characteristic laws and differences between normal frequent trajectories and different abnormal trajectories.
(3) By comparing the difference between the characteristic index predicted by the trajectory and the threshold value of the trajectory abnormality evaluation index, the abnormality of the trajectory to be measured is analyzed, and the final trajectory abnormality detection result is obtained.

Next, an example is given to explain our estimation method of abnormal trajectory. Through the historical trajectory data, the difference analysis of the evaluation indicators is carried out, and the threshold range of all trajectory abnormal detection evaluation indicators is obtained. In this paper, 50 groups of trajectory segments are selected and brought into the ADFA-LSTM model for training, of which 30 groups are normal trajectories from the historical vehicle trajectory data set collected by GPS; 20 groups are abnormal trajectory segments, including 10 groups of historical vehicle data generated by GPS alarm abnormal trajectory segment (yaw alarm, speeding alarm, etc.), 10 groups are simulated road yaw abnormal trajectory segments. Analyze the characteristic of the trajectories through the value range and the overall trend of the characteristic indicators of different trajectory segments. The error rate and mean square error of the normal trajectory and abnormal trajectory are shown in Fig. 3.



(a) Trajectory offset rate



(b) Mean square error of trajectory

Fig. 3. Threshold range of indicators for different track segments

According to Fig. 3, it can be seen that there are obvious differences in the value ranges of the two types of indicators for the normal trajectory segment and the abnormal trajectory segment. Among them, the value range of the trajectory offset rate (E) of the normal trajectory segment is basically maintained in the interval [0, 0.03], and the value range of the mean square error (MSE) is basically maintained in the range of [0, 0.0015]. The value range of the trajectory deviation rate (E) of the abnormal trajectory segment fluctuates in the interval of [0.04, 0.08], and the value range of the mean square error (MSE) fluctuates in the interval of [0.003, 0.006]. Therefore, it can be assumed that when the trajectory deviation rate E < 0.04 and the mean square error MSE < 0.002, the deviation between the measured trajectory segment and the normal frequent trajectory is small, and the trajectory is judged to be a normal state. When the trajectory deviation rate E > 0.08 or the mean square error MSE > 0.007, it is judged that there may be abnormal data in the trajectory segment. When the value of the trajectory deviation rate E is in the interval [0.04, 0.08] or the value of the mean square error MSE is in the interval [0.002, 0.007], the deviation between the measured trajectory segment and the normal frequent trajectory is large, and the vehicle may have unsafe behavior, which is judged that the trajectory is abnormal.

4 Experiments and Analysis

4.1 Experimental Data Set and Evaluation Criteria

According to the vehicle trajectory data and road characteristics, this paper divides the abnormal trajectory detection results into two categories: data abnormality and trajectory abnormality. Data abnormalities include various GPS data errors caused by the process of collection, transmission and storage; and abnormal trajectories are based on the true and reliable GPS data, and the trajectory characteristics are quite different from the normal frequent trajectory. This difference is certain. To a certain extent, it implies the behavior of the vehicle's abnormal driving.

In this paper, the mean square error (MSE) is used to verify the prediction ability of the model. The smaller the value of MSE is, the better the accuracy of the prediction model is. At the same time, the trajectory deviation rate (E) is introduced and combined with MSE to judge the deviation degree between the predicted position and the normal trajectory, and used as the evaluation index of trajectory anomaly detection.

The formula of trajectory offset rate is as follow:

$$E = \frac{P_{\mathrm{real}} - P_{predict}}{P_{real}/100} \tag{1}$$

The formula of mean square error is as follow:

$$MSE = \frac{1}{N}\sum_{t=1}^{N}\left(P_{real_t} - P_{predict_t}\right)^2 \tag{2}$$

Where N is the number of samples, P_{real} is the normal value, and $P_{predict}$ is the predicted value.

4.2 Test and Analysis of Traffic Trajectory Anomaly Detection Model

This section mainly includes two experiments. The first experiment is the improvement experiment of FA algorithm. The FA algorithm is optimized by different methods and applied to the LSTM prediction model to test the effectiveness of ADFA algorithm. The second experiment is the comparison of ADFA-LSTM and other common LSTM improved algorithms to test the prediction accuracy of the model and verify the recognition ability of the model.

The data used in the experiment in this section is from the GPS trajectory data of operating vehicles collected in the actual project, including about 40,000 trajectories. These data can be used as experimental data in this paper because they represent the route and topological structure of most operating vehicles.

Table 2. Vehicle GPS track data segment

UnitID	GPS Date	GPSTime	Longitude	Latitude	Height (m)	Speed (km/h)
6	20180403	16:59:14	111.546637	41.285371	916	60
6	20180403	16:59:44	111.547987	41.289561	917	61
6	20180403	17:00:14	111.549214	41.294636	912	56
6	20180403	17:00:44	111.548915	41.299101	911	55
6	20180403	17:01:14	111.549035	41.301745	891	65
6	20180403	17:01:44	111.549681	41.303357	889	58

Table 2 shows a data segment of a trajectory generated on April 3, 2018 for a vehicle with GPS equipment No. 6. A complete vehicle trajector contains amount of position points, each of which contains information such as vehicle ID, timestamp, longitude and latitude, altitude and speed.

The first experiment uses different methods to optimize the standard FA algorithm, and applies it to the LSTM prediction model to test the effectiveness of ADFA algorithm to improve the LSTM network structure.

The standard firefly algorithm (FA) mainly includes three steps: population initialization, population flight to brighter individuals and determination of optimal firefly position. However, the fixed step factor and the brightest individual remain unchanged during initialization, which will lead to the oscillation of the result, and it is difficult to achieve the optimal effect. Therefore, this paper adds the adaptive step factor and the brightest individual to optimize the FA algorithm, in which the brightest individual is mainly perturbed once and perturbed N times respectively, and the adaptive step factor is calculated by two adaptive functions, respectively:

$$\alpha(t+1) = \left(1 - \frac{t}{T_{\max}}\right) \cdot \alpha(t) \tag{3}$$

$$\alpha(t+1) = \alpha(t) \cdot \exp\left(-\frac{k \cdot t}{T_{\max}}\right) \tag{4}$$

Formula (3) and Formula (4) represent adaptive function 1 and adaptive function 2 respectively. In this paper, the ADFA algorithm selects the brightest individual disturbance once in combination with adaptive function 2 to optimize the standard firefly. In the comparison experiment, the original FA algorithm is used to establish the FA-LSTM model, and the FFA1-LSTM and FFA2-LSTM models are established based on adaptive functions 1 and 2 respectively. The brightest individual behavior is improved by perturbation once and disturbance N times, and the DFA1-LSTM and DFA2-LSTM models are established respectively. Comparison results of final model prediction mean square error are shown in Fig. 4.

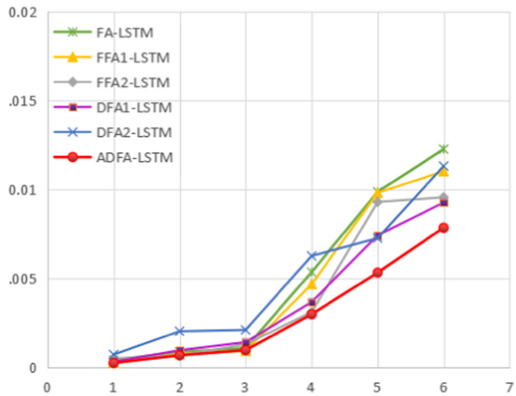


Fig. 4. Comparison of average error of FA algorithm optimization model

According to the growth rate of overall mean square error in Fig. 4, the order is: FA-LSTM > FFA1-LSTM > DFA2-LSTM > FFA2-LSTM > DFA1-LSTM > ADFA-LSTM. It can be seen that the growth rate of the unmodified FA-LSTM model is the fastest, followed by the FFA1-LSTM model and the DFA2-LSTM model with the adaptive function 1 and the brightest individual disturbance N times, and the growth rate of the FFA2-LSTM model and the ADFA1-LSTM model with the adaptive function 2 and the brightest individual disturbance once is relatively slow. It can be seen that the optimization effect of the adaptive function 2 is better than that of the adaptive function 1 after playing the role of the local exploration of the optimal individual. The prediction effect after adding the disturbance factor is obviously smaller than that of the unmodified FA algorithm, and the prediction accuracy of the first disturbance is higher. The ADFA algorithm proposed in this paper has better optimization effect on the LSTM model.

The second experiment is the comparison between ADFA algorithm and other commonly used LSTM improved algorithms, which verifies that the proposed ADFA-LSTM algorithm has better prediction effect, and then tests the recognition ability of each model for abnormal trajectory. In this paper, particle swarm optimization (PSO) and longicorn whisker algorithm (BAS) are selected as the comparison algorithm. In order to verify the effectiveness of the improved algorithm, four models, LSTM, PSO-LSTM, BAS-LSTM and ADFA-LSTM, are established in this paper for experimental test to verify the optimization ability of each algorithm to the model. The mean square error of the experimental results is shown in Table 3.

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According to the trend of prediction results, the overall trend of this model is closer to the real value, and the prediction difference is the smallest. According to the accurate

Table 3. Prediction mean square error of LSTM improved model

Mean square error	First point	Second point	Third point	Fourth point	Fifth point	Sixth point
LSTM	0.000587	0.000987	0.001637	0.002867	0.009878	0.025442
ADFA-LSTM	**0.000288**	0.000588	**0.001293**	**0.001723**	**0.003694**	**0.008584**
PSO-LSTM	0.000397	**0.000579**	0.001336	0.003824	0.007331	0.016439
BAS-LSTM	0.000439	0.000839	0.001699	0.002773	0.009967	0.023831

value of the mean square error in Table 3, the comparison is as follows: ADFA-LSTM > PSO-LSTM > BAS-LSTM > LSTM, and the best value of each step represented by bolding is that the predicted value of each model at the first few points is relatively close. But with the increase of the number of prediction steps, the growth rate of the mean square error of this model is the slowest, and the prediction effect is more stable.

Next, the recognition ability of each model for abnormal trajectory is verified. The abnormal trajectory point is simulated based on the normal frequent trajectory, and the abnormal point detection is carried out by using the abnormal index estimation method in Sect. 3.5, and the reliability of the model is measured by the detection accuracy rate of abnormal points and the false detection rate of normal points. The specific formula is as follows:

$$\text{Outlier accuracy} = \frac{\text{Correctly identify the number of abnormal points}}{\text{Total number of abnormal points}} \times 100\% \tag{5}$$

$$\text{False detection rate of normal points} = \frac{\text{Number of false detection points}}{\text{Total number of normal points}} \times 100\% \tag{6}$$

The test results of each model are shown in Table 4.

Table 4. Abnormal trajectory detection results of LSTM improved model

Model name	Track offset rate		Mean square error		Outlier accuracy	False detection rate at normal points
	Normal point	Outliers	Normal point	Outliers		
LSTM	0.036244	0.046825	0.001623	0.003246	77.3%	3.89%
ADFA-LSTM	0.019386	0.053613	0.000541	0.004677	89.1%	1.44%
PSO-LSTM	0.026832	0.050388	0.000977	0.004108	85.8%	1.87%
BAS-LSTM	0.036244	0.049931	0.001038	0.003986	81.4%	2.68%

According to the test results in Table 4, compared with other models, the ADFA-LSTM model in this paper has the lowest evaluation index value (including trajectory deviation rate and mean square error) at the normal point, while the evaluation index value at the abnormal point is higher. Since the predicted value of the model is more biased towards the normal value in the training set, the higher the evaluation index value of the abnormal point, the easier it is to reach the abnormal detection threshold, and then the abnormal trajectory point can be identified earlier and more accurately. The trajectory points have strong recognition ability.

5 Conclusion

With the rapid development of the economy, the number of road traffic mileage and highway density are continuously increasing, and the problems of road traffic safety are becoming more and more prominent. In recent years, the number of casualties caused by traffic problems has consistently ranked first in the world. How to dig out the behaviors and factors related to road traffic safety to realize the early warning of the safety behaviors of vehicles so as to reduce the incidence of traffic violations and accidents, is a very hot topic. In this paper, aiming at the problems caused by the complexity of vehicle GPS trajectory for abnormal trajectory analysis, a LSTM trajectory prediction model based on bionic neural network is proposed. At the same time, in order to solve the shortcomings of LSTM easy to fall into local optimality, an adaptive function is proposed. The Firefly Algorithm (ADFA) perturbed by the brightest individual optimizes the LSTM network structure, and recognizes abnormal trajectories based on the prediction results. Finally, the effectiveness of the proposed method is verified by experiments.

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Author Queries

Chapter 8

Query Refs.	Details Required	Author's response
AQ1	Table will be printed in black and white, hence we have changed the red value to bold value in Table 3. Please check and confirm.	