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A Method for LSTM-Based Trajectory Modeling and Abnormal Trajectory Detection

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ABSTRACT Nowadays, massive data has been brought by the rapid development of technology. When finding whether trajectory to be detected is abnormal under the premise of given normal trajectories, we innovatively propose 1) Seq2Seq model based on LSTM prediction network for trajectory modelling (SL-Modelling), and 2) abnormal trajectory detection method with spatio-temporal and semantic information. Firstly, SL-Modelling is used to obtain sequence-type trajectory models of normal trajectory groups directly for subsequent detection with no need to extract a large number of features manually and adapting to different sequence length. Then we introduce the concept of distance and semantic interest sequence that makes full use of spatio-temporal and semantic information of trajectories. Finally, the similarity between models and trajectory to be detected is calculated to detect abnormal trajectory. The experimental results of publicly available flight data set show that trajectory models obtained are descriptive enough to represent normal trajectory groups well, and the accuracy of modelling is higher than the existing advanced methods. Besides, the detection with spatio-temporal and semantic information has been verified that it has stronger detection ability with higher accuracy and takes less time.

INDEX TERMS LSTM prediction network, trajectory modelling, abnormal trajectory detection, spatio-temporal information, semantic information.

I. INTRODUCTION

With the development of science and technology, the motion trajectory data gradually increases and becomes a significant branch of big data. The mining of trajectory data is extensively used in various fields of the national economy and national defence construction, such as target tracking, behaviour analysis, tourism and navigation. When the trajectory is influenced by its main body or external factors and has enough deviation from the model, it can be judged that the trajectory is abnormal. From the trajectory anomalies, we should have the capability to catch the point that helps us to find out the reasons and other meaningful attributes corresponding. Hence, detecting abnormal trajectory has significant practical value and has become one of the research hot spots [1].

Trajectory data take time, space and non-spatio-temporal attributes as the essential characteristics of moving objects, and reflect the spatial state evolution process of moving objects over time [2]. The existing abnormal trajectory detection studies pay more attention to classification according to the behaviour characteristics of the trajectory and increase the workload of hand-crafted feature extraction.

To summarize the trajectory data we need to process now, we can find that they have the following characteristics: 1) existing as sequence-type data, 2) big data and multi-dimensions, 3) high correlation degree of previous and present events with a causal relationship, 4) a descriptive question. We hope to find a way to adapt and process the data with these characteristics while reducing our workload and allowing us to get the results more directly and more conveniently. In this case, long-short term memory (LSTM) provides a solution to the problem.

Research in the field of deep learning shows that deep learning algorithm is capable of learning data features directly [3]. Meanwhile, LSTM, a variant of the recurrent neural network (RNN) in deep learning, shows excellent learning ability in sequence data due to its structural characteristics [4], [5], and recent research also shows that LSTM-based method can be a good choice for exploring and solving problems about movement [6]. Therefore, with the help of LSTM, we can focus on the previous and present trajectory sequence data at the same time, and learn the

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causality of the data independently. Even in the face of a large amount of data, it is no longer necessary to manually extract the data features, so the trajectory groups can be described in sequence-type for modelling directly.

At the same time, in addition to considering trajectory spatio-temporal information as many recent studies focus, the semantic trajectory can provide more valuable application and contextual information for trajectory analysis, which makes semantic trajectory data analysis receive extensive attention in recent years [7]. However, the existing analysis of semantic trajectory information is mostly limited to the main body and fails to extend the concept of semantics.

In this paper, our contributions are as follows:

1 *Trajectory modelling.* With the help of SL-Modelling, we can directly obtain the sequence-type trajectory models of normal trajectory groups which adapt to different length of trajectory data and reduce the workload of extracting features manually.
2 *Abnormal trajectory detection.* The similarity between the trajectory model and the trajectory to be detected is calculated by combining trajectory spatio-temporal and semantic information in order to find abnormal detection.

The rest of this paper is organized as follows. In Section II, we introduce related work about LSTM based trajectory research and abnormal trajectory detection research and application. Section III proposes an abnormal trajectory detection method based on the LSTM prediction network, including SL-Modelling for normal trajectory groups and abnormal trajectory detection with spatio-temporal and the semantic information. Experiments in Section IV verify the feasibility and performance of the proposed method.

II. RELATED WORK

Abnormal trajectory detection means that when faced with multiple trajectories, an appropriate method is selected to find trajectories that are different from other trajectories in terms of shape, category and other characteristics. Obviously, mining abnormal trajectories directly from a large number of track group data has a heavy workload and low efficiency, which is necessary to set detection standards in advance according to experience. Therefore, this paper hopes to obtain the model of normal trajectory automatically first, and then directly compare the detected trajectory with the trajectory model, so as to complete the judgement of whether the trajectory is abnormal or not.

According to the analysis of the characteristics of trajectory data in the Section I, LSTM-based modelling method and the anomaly detection method combining spatio-temporal and semantic information can provide a way for us to solve the problem.

A. LSTM PREDICTION

At present, the trajectory data obtained usually show the characteristics of large scale and data density, and the data is composed of discrete points obtained by sampling, so it has the mathematical characteristics of both discrete and continuous. It is presented in the form of sequence. By combining sequence prediction and generative adversarial networks, Gupta *et al.* [8] constructed a recurrent sequence-to-sequence model to observe motion histories and predict future behaviour and used a novel pooling mechanism to aggregate information across people. Goh *et al.* [9] proposed a novel rough neural network-based model named radial basis function network with dynamic decay adjustment (RBFNDDA) to learn information directly from a data set and group it in terms of prototypes, and then, a neighbourhood rough set-based procedure was applied to detect prototype outliers. Song *et al.* [10] found the difficulty in learning the normal patterns and the problem of data sparsity and proposed anomalous trajectory detection using recurrent neural network (ATD-RNN) which learned the trajectory embedding to characterized the trajectory. Then, Cheng *et al.* [11] used coordinate sequence and spatio-temporal sequence and proposed spatio-temporal recurrent neural network (ST-RNN) and added attention mechanism.

Alahi *et al.* [12] proposed a social LSTM model based on LSTM network, which can learn general human movement and predict their future trajectories. It is in contrast to traditional approaches which use hand-crafted functions such as Social forces. Ren *et al.* [13] trained and tested LSTM network based on automatic identification system (AIS) to improve the accuracy of ship navigation behaviour prediction, and found that the prediction result based on LSTM network was of high accuracy, strong robustness and good generality. Fernando *et al.* [5] noticed that detecting abnormal events have been limited by using a variety of hand-crafted features, and recent research in recurrent neural networks had shown exemplary results in sequence-to-sequence problems such as neural machine translation and neural image caption generation. So they proposed a novel method to predict the future motion of pedestrian by combining the attention model. Xue *et al.* [14] focused on the vital role the scene layouts played and used three different Social-Scene-LSTMs (SS-LSTMs) to capture person, social and scene scale information. They also used a circular shape neighbourhood setting to improve prediction accuracy.

B. ABNORMAL TRAJECTORY DETECTION

The research of anomaly detection mainly has three aspects:

1) *What is the anomaly?*
2) *How to detect the anomaly?*
3) *How is the anomaly generated?*

The primary purpose of this research is to define the scope of normal behaviour as the detection standard, and then determine whether the data to be tested is abnormal [15], [16].

According to different application requirements and implementation principles, methods of abnormal trajectory detection are mainly divided into four categories: detection methods based on classification, detection methods based on historical value similarity, detection methods based on distance and detection methods based on mesh generation [17]. Historical value similarity can only be used to analyze and detect the historical trajectory data set. For example, time-dependent popular routes-based algorithm (TPRO) can be used to find all abnormal points in the historical trajectory data set. Mesh generation needs the support of urban road network, remote sensing and other related technologies, which can only be used in some applications. Zhu *et al.* [18] improved TPRO and proposed TPRRO, which introduced geospatial information to realize off-line and on-line real-time anomaly detection.

Most of the recent abnormal trajectory detection research focus on classification- and distance-based detection methods. One of the traditional methods of abnormal trajectory detection is to cluster the trajectory data [19]. If the trajectory does not belong to a specific class, it will be judged as an abnormal trajectory. Density-based spatial clustering of applications with noise (DBSCAN) is a classic method of clustering of applications with noise (DBSCAN) is a classic method of clustering. Duggimpudi *et al.* [20] analyzed the limitation of DBSCAN and proposed ST-DBSCAN and spatio-temporal behavioural outlier factor (ST-BOF) as the spatio-temporal extension of local outlier factor (LOF) to reduce the loss of detection accuracy during processing. General Potential Data Field (GPDf)-based trajectory clustering scheme has been adopted for detecting abnormal events such as illegal U-turn, wrong side and unusual driving behaviours, and it uses spatial and temporal attributes explicitly. Based on GPDf, Athanesious *et al.* [21] proposed general potential data field with spectral clustering (GPDfSC) which utilizes potential data field technique along with spectral clustering for effective identification of abnormalities.

Another is the calculation of deviation, which is mostly based on the definition of distance between trajectories. Typical distance calculation methods include Euclide distance, DTW, LCSS, and Hausdorff distance. Liu *et al.* [22] provided a distance function to calculate the degree of mismatch between two basic comparison units. They definded the concepts of matching and anomaly and then used R-Tree to find the mismatched unit, which will be judged as an anomaly. Jiang *et al.* [23] calculated the weighted multi-feature distance between the trajectory segments to cluster trajectories according to the trajectory deflection angle and velocity, and the anomaly detection is realized by comparing the trajectory information entropy. Yu *et al.* [24] proposed trajectory outlier detection algorithm based on common slices sub-sequence (TODCSS) which used a novel CSS distance calculation method with the length and time of trajectory and verified the accuracy and stability of the method on the Atlantic hurricane data set and real-life mobility trajectory data set.

Besides, some research on abnormal trajectory detection focus on neural network to tackle with large actual trajectory data. Yu *et al.* [25] proposed an abnormal trajectory recognition method based on BP neural network. They used the internal and external feature attributes of the trajectory as the input layer, and used trajectory similarity measure as output layer. Han *et al.* [26] proposed a trajectory outlier detection algorithm based on a bidirectional long-short term memory (Bi-LSTM) model which needs to extract six-dimensional motion feature vector and obtains the class type of the current trajectory points.

It is not difficult to find that the above researches are all based on the spatio-temporal information of the trajectory and its derived information (such as velocity, angle, etc.). They do not make full use of the semantic information of the trajectory. Trajectory semantic information reflects the user behaviour, state and preference in the generation of spatio-temporal data, including geographic location information, user behaviour information and hot event information [27]. In continuous space, it is more appropriate to add the semantic information with the spatio-temporal information together to fine-grained sequence processing [28], [29]. Parent *et al.* [30] summarized the framework of understanding trajectory semantics based on external data and expounded the applications of trajectory with semantic information.

Obviously, the analysis and processing of spatio-temporal information can be applicable to all cases, but in the case that there is some prior information or some semantic information is easy to extract. Making full use of semantic information can greatly reduce the workload of trajectory classification, and combing with spatio-temporal information can improve the accuracy of trajectory detection and prediction. Huang *et al.* [31] proposed a method of labelling the typical manipulating behaviour of air targets and considered that the multi-scale expression of trajectory semantics could be applied to the task of observing the historical activity patterns of targets. Roman *et al.* [32] considered that the context is important semantic information of the trajectory; the context-aware distance was proposed to detect the anomaly more efficiently. Cai *et al.* [33], [34] extended the original geographic trajectory pattern mining algorithm that returns the basic semantic trajectory and multi-dimensional semantic trajectory pattern.

Therefore, in this paper, each class of trajectories appearing in the group pattern is input into SL-Modelling to obtain the trajectory models. Then the trajectory models and the trajectory to be detected are combined to determine whether the trajectory to be detected is an abnormal trajectory with their spatio-temporal and semantic information.

III. ABNORMAL TRAJECTORY DETECTION BASED ON LSTM PREDICTION NETWORK

In this paper, the detection of abnormal trajectory mainly focuses on the overall or local data of a trajectory to analyze the difference between the trajectories, so as to judge the anomaly instead of analyzing points on trajectories. The whole abnormal trajectory detection is mainly carried out in two parts:

1 *Modelling for normal trajectory groups:* In order to detect abnormal trajectories, the first step is to determine the normal trajectory. Generally, consistent or similar trajectories appear in the data set in a group pattern, so it is

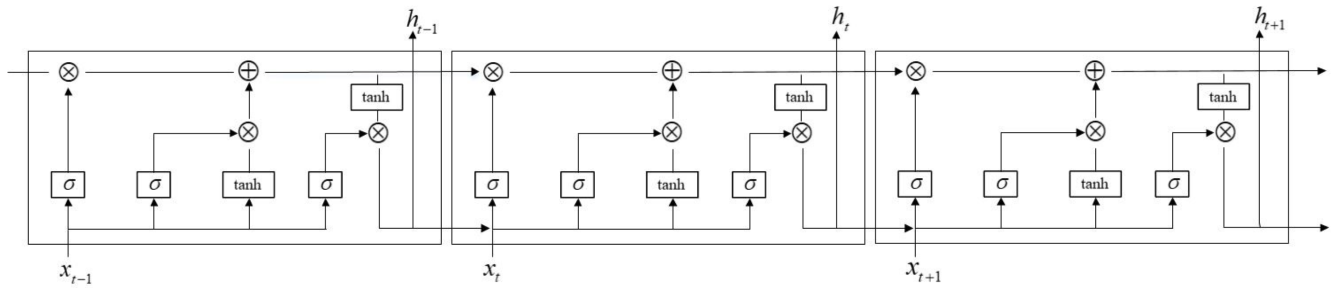


FIGURE 1. LSTM chain diagram.

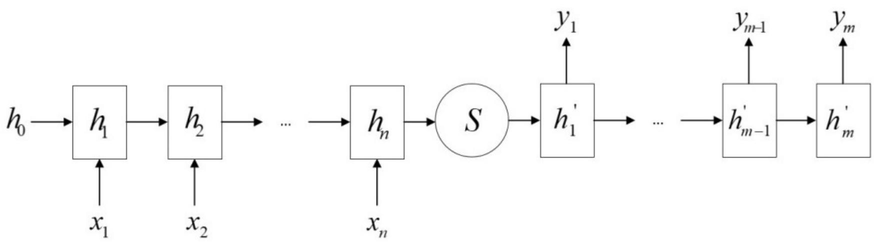


FIGURE 2. Seq2Seq mode.

necessary to find the most representative trajectories as the query trajectories for detection.

2 *Method for abnormal trajectory detection:* By making full use of the information carried by the trajectory data and combining the spatio-temporal and semantic information, the accuracy of detection will be improved, and the scope of detection objects will be expanded.

A. NORMAL TRAJECTORY MODELLING

In the process of trajectory modelling, multi-input multi-output (MIMO) model can be adopted. The input is multiple trajectories of the same group, the output is a predicted trajectory, and the predicted trajectory represents this trajectory group.

In practical application, we can find that the length of multiple trajectory data in the trajectory data set may not be the same, and there may be some problems such as missing data or different receiver working mechanism, resulting in data sparsity. When [10] researched on the same starting point trajectory modelling for trajectories with given departure and destination, they utilized some padding operations to align trajectories by using relevant trajectories. But this method needs enough prior knowledge of geography, increased the difficulty of data acquisition and data processing workload. And it cannot describe the reliability of the supplementary data.

Considering the learning ability of LSTM prediction network and the data length adaptability of Seq2Seq model, we propose SL-Modelling for normal trajectory modelling.

1) LSTM PREDICTION NETWORK

LSTM is a special type of RNN, which is born to overcome the gradient vanishing problem faced by RNN. Different from the single network layer of RNN, the unit state and cell state in LSTM module flow over time, and during the data flow, the structure of the gate controls the unit state to add or delete information.

It can be intuitively seen from FIGURE 1 that LSTM is a kind of chain network structure with repeated modules, and its structural characteristics determine that it is suitable for the processing of sequence data. When LSTM is dealing with the prediction of time series, different models can be adapted according to the needs.

2) SL-MODELLING

As shown in FIGURE 2, suppose $LSTMEncoder(\cdot)$ is the encoding function, and $LSTMDecoder(\cdot)$ is the decoding function, then at the time t, the input x_t, encoding state h_t, decoding state h'_t, hidden layer state S_t and output y_t satisfy

$$h_t = LSTMEncoder(x_t, h_{t-1}) \tag{1}$$
$$y_t = LSTMDecoder(y_{t-1}, S_{t-1}, h'_t) \tag{2}$$
$$S = f(h_1, h_2, \ldots, h_n) \tag{3}$$

In Eq. (3), context vector S is the hidden state of the decoding part and it only provides original state for the decoder rather than participating in subsequent operations. $f(\cdot)$ is the function to summarize information from encoder hidden layers and generate context vector for decoder.

FIGURE 3 demonstrates how SL-Modelling works. After LSTM Encoder receives the trajectory data, the LSTM module calculates and outputs the information of hidden layers according to Eq. (1). Then S is generated as the input of LSTM Decoder. Finally, we are able to obtain the modelling results formed by the output of decoder.

As shown in FIGURE 4, in the face of trajectory data set has access to, first of all, each normal trajectory group will be input into trained SL-Modelling respectively and get the K corresponding trajectory models. These models are used

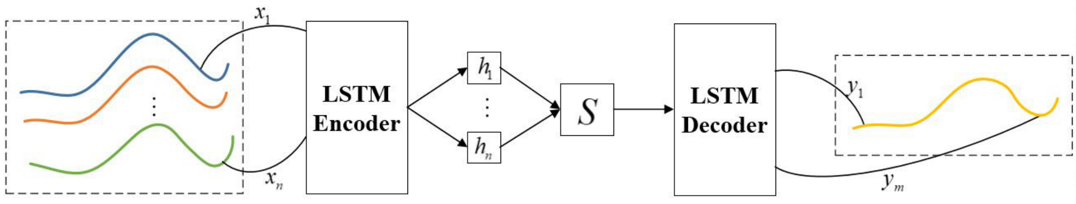


FIGURE 3. SL-Modelling.

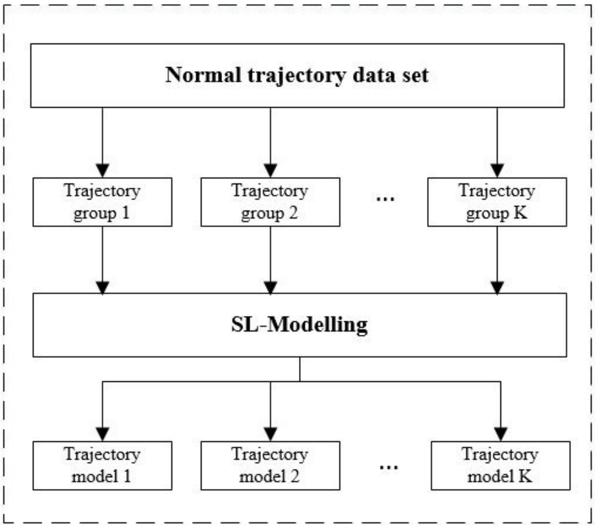


FIGURE 4. Trajectory modelling framework.

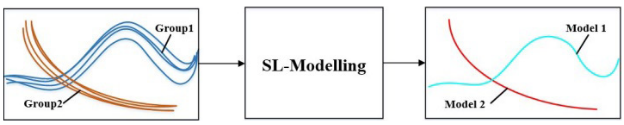


FIGURE 5. Modelling diagram.

to represent the standard for subsequent abnormal trajectory detection.

FIGURE 5 demonstrates modelling processing as a complement to FIGURE 4. The output of SL-modelling exists as sequence-type, which means we can apply the output as the trajectory models directly without any other processing.

By using SL-Modelling, it can complete a wider range of abnormal trajectory detection tasks and make trajectory modelling not limited to the problem of different length of historical trajectory data. It should be noted that we have proposed an effective mining method for normal trajectory group in previous research, so we will not discuss about it in this paper.

B. ABNORMAL TRAJECTORY DETECTION WITH SPATIO-TEMPORAL AND SEMANTIC INFORMATION

When mining and detecting trajectory data, the concept of trajectory similarity is usually introduced [35], and the distance between trajectory points or trajectory sequences (including sub-sequences) is used to describe the similarity between trajectories, which is important information for subsequent research.

The generation of trajectories of moving objects is subjective, which makes the trajectory carry spatio-temporal information and semantic information at the same time. Spatio-temporal information mainly refers to the position of the trajectory points in time and space, such as the latitude and longitude data obtained by the current satellite positioning system. In addition, the semantic information has more abundant meaning, including the trajectory direction, acceleration and deceleration behaviour, the region which the trajectories pass through, the movement preference of the moving objects, locator parameters, etc. It all can be analyzed as the semantic information of the trajectory. Therefore, we can use the spatio-temporal information and semantic information of trajectory for the study of abnormal trajectory detection simultaneously.

1) HAUSDORFF DISTANCE

Hausdorff distance is used to measure the degree of mismatch between two given point set. It can measure the shape similarity and is a better measurement method for the comparison of trajectory space information. In this paper, we focus on the difference in the overall shape between the trajectory model and the trajectory to be detected and judge whether the spatio-temporal difference is abnormal according to whether the difference is within the threshold range.

Assuming that point set $A = \{a_1, a_2, \ldots, a_m\}$ and $B = \{b_1, b_2, \ldots, b_n\}$ are known, the one-way Hausdorff distance from A to B can be expressed as

$$h(A, B) = \max_{a \in A}(\min_{b \in B}(\| a - b \|)) \tag{4}$$

The two-way Hausdorff distance between A and B is the maximum one-way distance between two sets, which is represented as

$$H(A, B) = \max(h(A, B), H(B, A)) \tag{5}$$

When detecting abnormal trajectory, assuming that the model of the normal trajectory is known, the spatial-temporal similarity between the trajectory to be detected P and the normal trajectory Q can be calculated by

$$Sim_{s-t}(Q, P) = \begin{cases} 1, & if\ H(Q, P) \leq th_{dis} \\ 0, & if\ H(Q, P) < th_{dis} \end{cases} \tag{6}$$

where th_{dis} is the detection threshold of trajectory spatio-temporal distance.

2) TRAJECTORY SEMANTIC INTEREST SEQUENCE

Position of Interest (POI) was originally used in the collection of the geographic information, which is a bridge connecting users with geographically meaningful points in the case of inaccurate knowledge of the geographical location and surrounding information. Trajectory POI is derived from the semantic information, and most of that is less time-dependent. With the development of semantic information acquisition technology, POI of trajectory is no longer limited to a certain place or a certain movement behaviour but extends to the key semantic information on the trajectory sequence. Based on the concept of POI, this paper proposes semantic interest sequence for trajectory data, which is used to calculate semantic similarity.

For example, for the navigation data obtained from ADS-B system, its semantic interest sequence can be established as < Type, Departure-Destination, Date, Register Number, ADS-B 24-bit Address Code >; For moving objects on the road, we can establish a semantic interest sequence as <Vehicle, Date, Device parameters >. The vehicle can be cars or underground, and device parameters are the electronic equipment with locating function and their related parameters.

Then, given the trajectory data set T, the semantic interest sequence of each trajectory is established as $\{SI_1, SI_2, \ldots, SI_m\}$. SI_i is the semantic interest sequence of each trajectory and $i = 1, 2, \ldots, m$. m is the number of trajectories in the data set. Set $SI_i =< SI_{i1}, SI_{i2}, \ldots, SI_{in} >$ as semantic interest sequence of the i trajectory, and n is the amount of valuable semantic information in the trajectory. The semantic similarity of SI_i and SI_j can be calculated as

$$sim(ik, jk) = \begin{cases} 1, & if \ SI_{ik} = SI_{jk} \\ 0, & if \ SI_{ik} \neq SI_{jk}, k = 1, 2, \ldots, n \end{cases} \tag{7}$$

$$Sim_{sem}(i, j) = \frac{1}{n}\sum_{k=1}^{n} sim(ik, jk) \tag{8}$$

3) ABNORMAL TRAJECTORY DETECTION ALGORITHM

The anomaly judgement processing of the trajectory to be detected is to compare the similarity between the trajectories to be detected and the trajectory models with the spatio-temporal information and semantic information. Whether the trajectories to be detected are abnormal will be judged that depending on similarity. The abnormal trajectory detection algorithm is listed in TABLE 1, and the detection diagram is shown in FIGURE 6.

Let length of the semantic interest sequence be n. In the whole abnormal trajectory detection processing, for K trajectory models and N trajectories to be detected, it needs to calculate KN distances between trajectories. Therefore, the time and space complexity of the spatio-temporal similarity algorithm are all $O(KN)$. Since it is necessary to compare each element of the semantic interest sequence, and saves only one semantic similarity, the time and space complexity of the semantic similarity algorithm are respectively $O(KNn)$ and $O(KN)$. Finally, for abnormal trajectory detection with spatio-temporal and semantic information algorithm, the time complexity is $O(KN + KNn)$ and the space complexity is $O(KN)$.

In addition, Hausdorff distance is to measure the matching degree between two sets, and is not affected by the dimension of data. The content of the trajectory semantic interest sequence is determined by the type of the trajectory moving objects, so the subject of the trajectory spatio-temporal and semantic information is not limited. And, it can be used to calculate the similarity of various types of trajectory, such as transportation vehicles, pedestrians, natural migration.

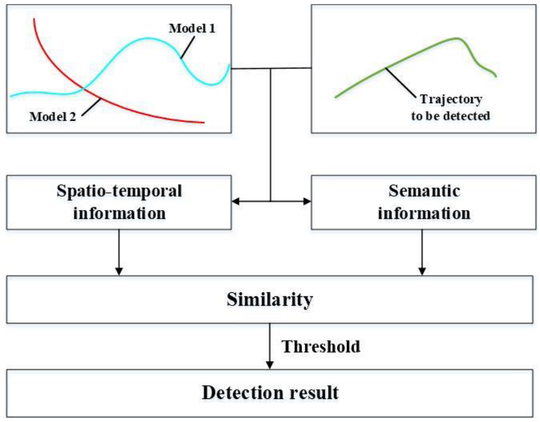


FIGURE 6. Detection diagram.

TABLE 1. Abnormal trajectory detection algorithm.

Algorithm: Abnormal trajectory detection with spatio-temporal and semantic information

Input: $traj_i, i = 1, 2, \ldots, K$ (trajectory models)
$P_j, j = 1, 2, \ldots, N$ (trajectories to be detected)

Output: $Abnormaltraj$ (results of abnormal trajectory detection)

Parameters: K (number of trajectory models)
N (number of trajectories to be detected)
th_{sim} (similarity detection threshold)
$Sim_{s-t}(\cdot)$ (spatio-temporal similarity function)
$Sim_{sem}(\cdot)$ (semantic similarity function)
ω_1 , ω_2 (weight factors, and ω_1、 $\omega_2 \in [0, 1]$)

```
for P_j = 1 to N do
    Index ← 0
    for Traj_i = 1 to K do
        calculate Sim_{s-t} and Sim_sem between Traj_i and P_j
        Similarity ← ω_1 Sim_{s-t} + ω_2 Sim_sem
        if Simlarity > th_sim then
            Index ← Index + 1
        end if
    end for
    if Index = K then
        Abnormaltraj ← {P_j}
    end if
end for
return Abnormaltraj
```

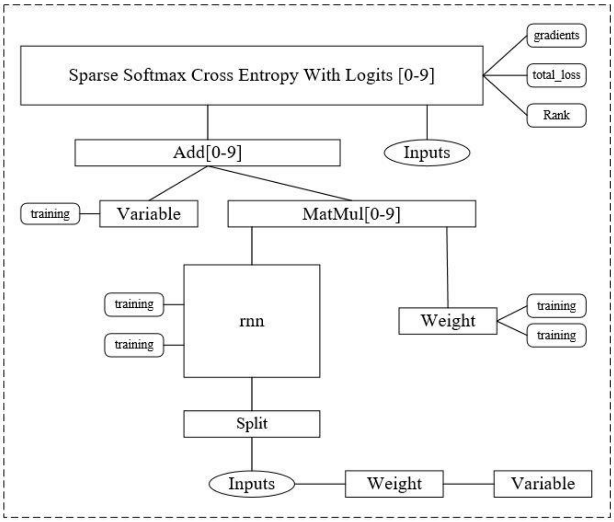


FIGURE 7. LSTM prediction network structure.

So that the anomaly detection method has a universality to be applicable to a variety of types of trajectories.

IV. EXPERIMENTS

In the experiments, we construct the data set with publicly available flight trajectory data from Flightradar24, and verify the feasibility and related performance of the SL-Modelling for normal trajectory groups and abnormal trajectory detection with spatio-temporal and semantic information proposed in this paper.

A. LSTM PREDICTION NETWORK MODEL

The experimental platform is based on the PC terminal of Intel®Core^{TM}i5 cpu2.50ghz and 8GB RAM, and the operating system is Windows 10. Python 3.6 and Tensorflow 2.0 are used to complete the programming implementation of the model.

According to the model visualization of Tensorboard, the model structure is shown in FIGURE 7.

B. EXPERIMENTS AND DISCUSSION OF SL-MODELLING FOR NORMAL TRAJECTORY GROUPS

Flightradar24 is application software that can provide real-time and historical flight information data to users. It uses ADS-B system to obtain and transmit flight information and can provide the longitude and latitude, departure, destination, flight altitude, ICAO24-bit address and other information of the entire route.

In the Experiments, we choose flight between October - December 2019, CA1370 (SYX-PEK), CZ6717 (SYX-PEK), HO1128 (SYX-SHA), MU2728 (SYX-SHA) and NS8012 (SYX-PEK) trajectory data as No.1 ~ No.5 normal trajectory groups. Each group contains 20 trajectory data set that selected randomly and contains more than 5000 data points, as shown in FIGURE 8. For the convenience of observation, the longitude and latitude are displayed in the form of plane coordinates, with the horizontal coordinate representing the east longitude and the vertical coordinate representing the north latitude.

1) SL-MODELLING RESULTS

For the trajectory modelling task, the trajectory models obtained should not only ensure the accuracy, that is, the error with the normal trajectory groups of the modelling is small enough, but also fully reflect the motion characteristics and trend in the whole trajectory movement process, so as to enhance the representativeness of the models. Five types of normal trajectory groups were fed into the trained SL-Modelling, and the bold red line in the FIGURE 9 is the predicted results of trajectory models.

It can be found that the trajectory model obtained by using SL-Modelling for normal trajectory groups proposed in this paper can well reflect the direction change in the trajectory, and is not affected by the special case of a small amount of sub-trajectory deviating from the original course, which indicates that the models can effectively represent the normal trajectory groups.

2) COMPARISON AND DISCCUSION

To verify the performance, we compare the performance of SL-Modelling with that of ATD-RNN proposed by [9], gradient descent (GD) proposed by [25], BP neural network proposed by [24] and nonlinear autoregressive neural network (NAR) which is mature and widely applied in prediction.

Mean square error (MSE) (satisfy as followed) and average running time (ART) are used as performance indexes.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{L}(x_{ij} - \hat{x}_j)^2 = \frac{1}{N}\sum_{i=1}^{N}(\left\|\boldsymbol{X_i} - \hat{\boldsymbol{X}}\right\|_2)^2 \tag{9}$$

where N is the number of normal trajectory groups, $\boldsymbol{X_i}$ is data matrix of normal trajectory, and $\hat{\boldsymbol{X}}$ is the data matrix of model.

TABLE 2 and TABLE 3 respectively show the MSE and ART of network training for 100 times about the modelling results of the No.1~No.5 normal trajectory group by SL-Modelling, ATD-RNN, NAR, BP and GD. It is not difficult to find: 1) The modelling error of SL-Modelling is the smallest, and the time is the longest. 2) The running time of SL-Modelling, ATD-RNN and NAR is similar, but SL-Modelling performs best; 3) Although the running time of BP and GD is small, the error of the modelling results is approximately 47.7 times as large as that of SL-Modelling in average.

According to comprehensive experimental results, SL-Modelling for normal trajectory groups, compared with other existing methods, the modelling result is better and has higher accuracy. It can better reflect and predict motion trend and characteristics of trajectory, and the trajectory model is not affected by a small number of special circumstances. It means that the models are representative and able to provide

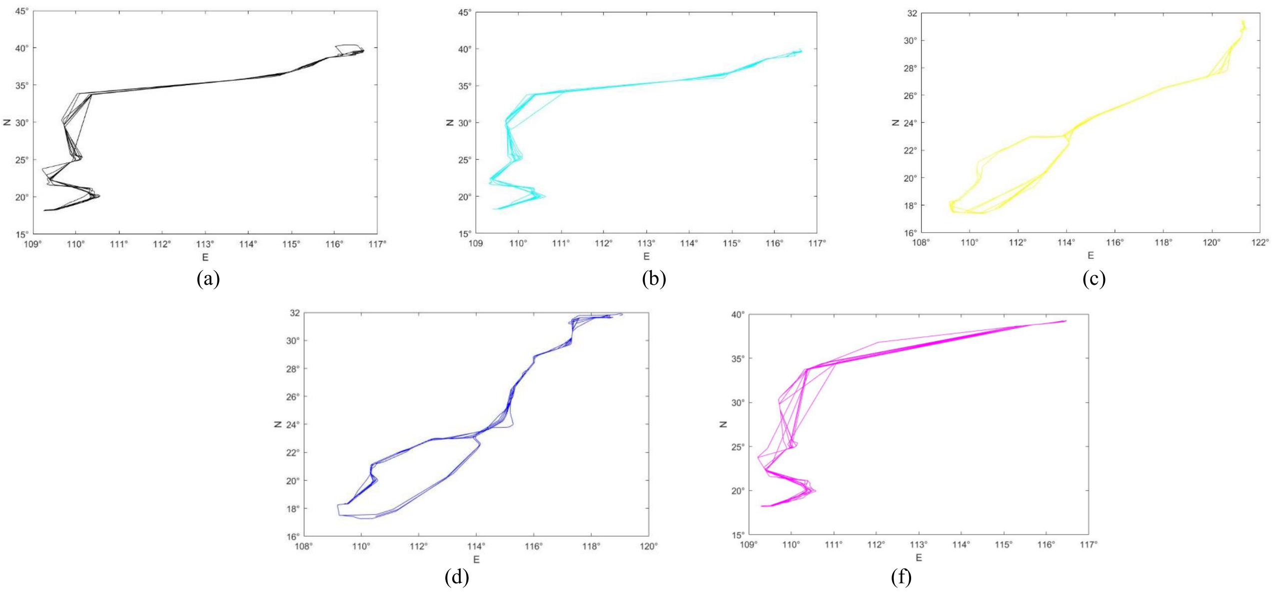


FIGURE 8. (a)~(f) are plane coordinates of trajectory data of flight CA1370, CZ6717, HO1128, MU2728 and NS8012 respectively.

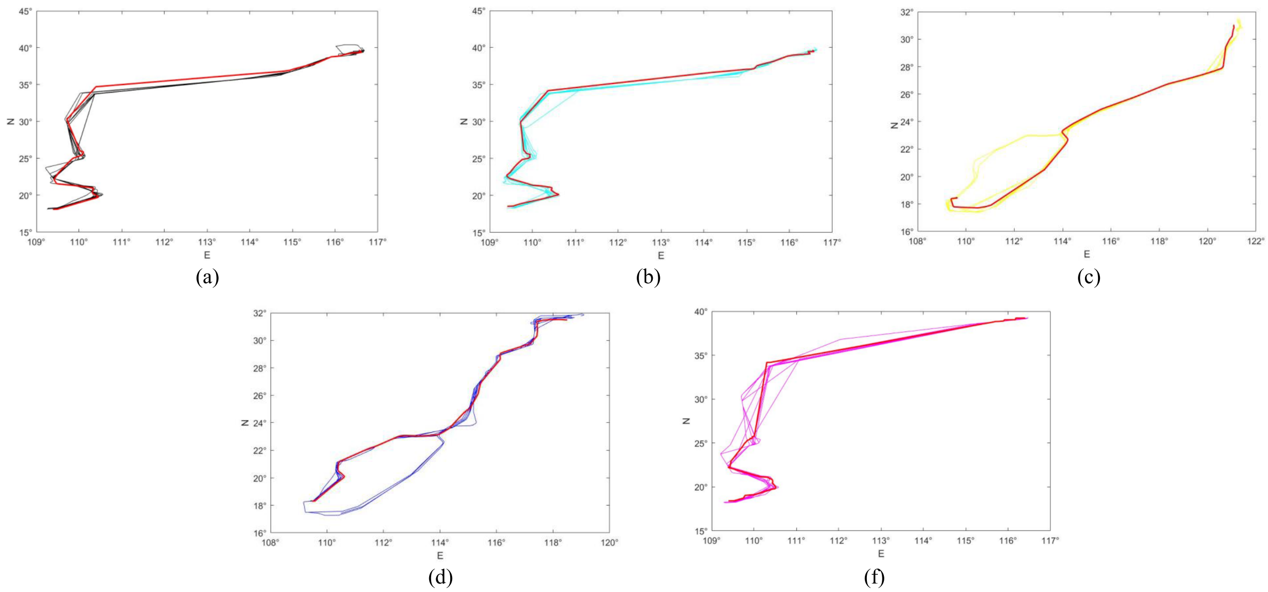


FIGURE 9. (a)~(f) are plane coordinates of trajectory modelling of flight CA1370, CZ6717, HO1128, MU2728 and NS8012 respectively.

TABLE 2. Results of MSE calculation.

Performance index	Group label	SL-Modelling	ATD-RNN	NAR	BP	GD
MSE	1	0.666	0.702	1.045	9.819	20.450
	2	0.021	0.038	0.664	12.808	13.040
	3	0.069	0.089	0.503	12.161	13.323
	4	0.240	0.337	0.659	16.425	18.923
	5	0.755	0.829	2.000	28.344	21.922

precise data and information support for the following application process.

Although the training of SL-Modelling takes the longest time, SL-Modelling for normal trajectory groups proposed in this paper can be a better choice under the premise of low real-time requirement in combination with its accuracy.

C. EXPERIMENTS AND DISCUSSION OF ABNORMAL TRAJECTORY DETECTION

On the premise of known trajectory models, it just needs to calculate the similarity between trajectories to be detected and models in order to realize the comparison. If the similarity is less than the threshold, it means that the trajectory to

TABLE 3. Running time of experiments.

Performance index	SL-Modelling	ATD-RNN	NAR	BP	GD
ART(s)	22'36	21'82	21'00	8'40	8'42

TABLE 4. Semantic interest sequnce of models.

Group label	Type	Departure-Destination	Mode	Code
1	A321	SYX-PEK	7811A6	4273
2	B737	SYX-PEK	4803F8	4264
3	A321	SYX-SHA	7805C4	5660
4	A319	SYX-SHA	780C25	4270
5	B738	SYX-PEK	780E68	0

TABLE 5. Results of anomaly detection with spatio-temporal and semantic information.

		Sample truths		Total
		Normal	Abnormal	
Predicted	Normal	251	15	266
	Abnormal	17	87	104
Total		268	102	370

TABLE 6. Results of anomaly detection based on TODCSS.

		Sample truths		Total
		Normal	Abnormal	
Predicted	Normal	207	30	237
	Abnormal	30	103	133
Total		237	133	370

TABLE 7. Performance comparison.

Performance index	Abnormal trajectory detection with spatio-temporal and semantic information	Abnormal trajectory detection based on TODCSS
Accuracy	91.351%	83.784%
Precision	85.294%	77.444%
ART(s)	111'74	176'86

be detected is similar to the model. On the contrary, this trajectory to be detected will be judged to be abnormal. By the time we acquire all detection results, the abnormal trajectory detection task will have been finished.

In the experiment, the flight routes SYX-PEK and SYX-SHA were set as normal trajectory groups respectively, and the anomaly detection method mentioned in this paper was cross-verified. All trajectory data in the data set were compared with trajectory model No.1, No.2, No.5 and model No.3, No.4 respectively, and a total of 370 test samples were constituted. As shown in FIGURE 10, the pink line is the normal trajectories, the black line is the trajectory model, and the blue line is the abnormal trajectories.

TODCSS proposed in [23] is a measurement method for similarity of trajectory spatio-temporal data. It sets a threshold value for the distance of the trajectory pair. If the distance between the corresponding sub-trajectories on two trajectories is greater than the threshold, it determines that there is an anomaly on the sub-trajectory and returns all the abnormal sub-trajectories. By comparing abnormal trajectory detection with spatio-temporal and semantic information in this paper and TODCSS, the results are shown in TABLE 5 and TABLE 6. In TABLE 7, accuracy, precision and ART are used as performance indexes for comparison and analysis.

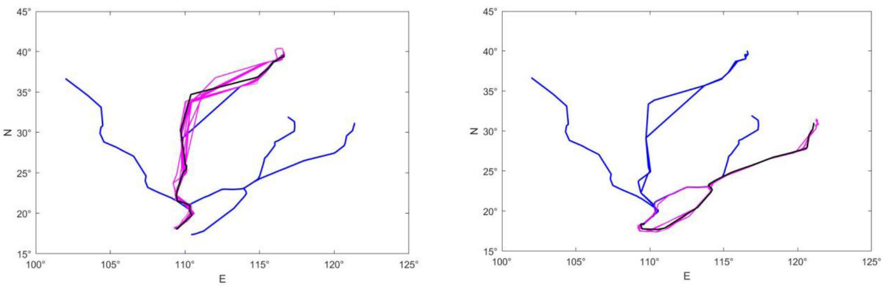
$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{10}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{11}$$

where TP, FP, TN and FN represent true positive, false positive, true negative and false negative respectively.

It should be noted that, in this experiment, the abnormal trajectory detection method with spatio-temporal and semantic information is to analyze and calculate the spatio-temporal data and semantic data of the trajectory in the data set, while the TODCSS only focus on the abnormal trajectory in spatio-temporal, without considering the semantic information of the trajectory.

According to the actual situation of the experimental data set, the detection threshold of the trajectory spatio-temporal



(a) (b)

FIGURE 10. (a) and (b) are abnormal trajectory detection diagram.

distance th_{dis} is set as 4.0235, and the similarity detection threshold th_{sim} is 0.85. The semantic interest sequence of 5 models selected for the experiment are shown in TABLE 4. The semantic interest sequence of 5 trajectory models and trajectories to be detected will be extracted as $<$ Type, Departure, Mode, Code$>$ for semantic similarity calculation.

After analysis and comparison, it is found that the abnormal trajectory detection method proposed in this paper is better than the TODCSS method in the judgment of normal and abnormal samples. Even if considering the trajectory semantic information, the amount of data needs to be processed is larger, but the abnormal trajectory detection with spatio-temporal and semantic information still has stronger detection ability with higher accuracy and takes less time.

V. CONCLUSION

The novelty of this paper lies in the use of SL-Modelling to model the normal trajectory groups and in detecting the abnormal trajectory with spatio-temporal and semantic information. We focus on the overall trajectory data and apply the SL-Modelling for trajectory sequence processing. Different from traditional methods, SL-Modelling provides sequence-type modelling results directly, has no need to extract features manually and is no longer limited by the difference in the length of trajectory data that making trajectory modelling processing more adaptive. After obtaining the trajectory model, Hausdorff distance and semantic interest sequence are introduced to calculate the spatio-temporal and semantic similarity of the trajectories to be detected and the trajectory models, and then the weighted values of the two are compared with the threshold. If the similarity value is higher than the threshold, the trajectory to be detected can be judged as an abnormal trajectory. Moreover, the distance calculation and semantic interest sequence extraction in this method can be applied to various types of trajectories of different subjects. The proposed method has performed its feasibility and performance in the publicly available flight data set. The experiment results show that the accuracy of SL-Modelling is higher than other trajectory modelling and prediction methods. The models are so descriptive to be able to better reflect the motion characteristics and trend of the trajectory which means strong representativeness and is not affected by the special case of a small amount of sub-trajectory deviating from the original course. And then, the abnormal trajectory detection with spatio-temporal and semantic information has been verified that it has better detection effect, shorter time and stronger detection capability than the current mature detection method.

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