Trajectory Prediction of Vessels based on Data Mining and Machine Learning

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ABSTRACT: *With the development of marine traffic information digitalization, proactive information service has become increasingly important in maritime intelligent traffic systems (ITS). Trajectory prediction is one of the kernel problems that must be addressed to realize proactive information service. This study proposes an intelligent model to solve the issue of the trajectory prediction of vessels based on data mining and machine learning methods. The spatial clustering algorithm of data mining is used to cluster the historical trajectories of vessels, and the cluster results represent the distribution patterns of these historical trajectories. The support vector machine algorithm of machine learning is used to train the classifiers. The classifiers define the pattern of the new trajectory of the vessel, which must be predicted. In the experiment, the information on 2862 trajectories is used as input to the model in chronological order to simulate the data flow in real-time situation. The predicted trajectories are compared with the actual trajectories of vessels. Experimental results show that future trajectories can be predicted efficiently and accurately. The intelligent model can also solve prediction problems with little human intervention and can automatically adapt to dynamic applications. The prediction results can provide accurate and reliable data for proactive information service. The model promotes the development of maritime ITS.*

Subject Categories and Descriptors
K.2.8 [Database Applications]: Data mining; **B.2.4 [High-Speed Arithmetic]:** Algorithms

General Terms: Data Mining, Machine Learning, Intelligent Traffic Systems

Keywords: Trajectory prediction, Spatial clustering, Data mining, Support vector machine, Machine learning

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1. Introduction

A trajectory is generally considered to be a line that is generated from a series of sequential points. Each point is a record of the position of a moving object and other attribute information, such as time, speed, direction, and others [1]. The purpose of trajectory prediction of vessels is to calculate the future trajectory of vessels, which is a highly valuable piece of information because it facilitates the provision of important information on warnings related to traffic conditions, traffic control and planning, and others. At present, information on the movement of vessels is increasingly detected, collected, and stored in databases. One of the important applications based on the big data is prediction [2–4]. With the explosive growth of traffic data, more and more data forms are now available to people. However, some problems still occur, such as data noise, loss, error, diversity, and so on. Trajectory data are often provided in the form of a data stream. Thus, methods that solve these problems and exploit huge amounts of the data stream must be developed to predict the trajectories of vessels. The model should not only be able to deal with real-time data but should also have noise immunity. This study conducts work to satisfy these requirements.

2. State of the Art

Two main methods can be used to predict the future trajectory of a moving object. The first method uses motion functions to predict the next location of a moving object. The second method predicts the future trajectory of a moving object based on the historical information of its motion.

The first method has good accuracy when the specified future time is close to the current time and the speed, course, environmental influence, and other factors are known. However, this method is not very effective in long-term location prediction [5]. A typical approach based on this method is the linear motion function; another is the nonlinear motion function.

The prediction results of the second method in both near and distant future time prediction show significant improvement. However, this method is applicable only when sufficient historical records exist. A typical approach of the second method is to divide the space in which the object moves into several small cells, and each small cell is regarded as a node [6–16]. The trajectory of a moving object is described as a series of nodes when it goes through the nodes in the space one by one. The transition probability of an object moving from one node to another is calculated. The future trajectory can be predicted based on the nodes and their transition probability information. Jeung et al. divided historical trajectories into different groups by time and found the regions where the moving objects always pass [5]. These frequented regions are the nodes. Lei et al. attempted to find the regions where the moving objects frequently pass and determined the size of each small cell using the QuadSection algorithm [1]. In contrast to the studies above, Sung et al. divided the raw trajectories into many subsequences and clustered them [17]. Their results consisted of several representative vector lines, and each vector was equivalent to a node.

Transition probability is always used to determine the patterns of trajectories. One typical model is the Markov model [1, 17–23], where the patterns of trajectories can be obtained, if the probability of an object moving from one node to another is known. The patterns are always described as a Bayesian tree, probabilistic suffix tree, and others. By indexing the patterns, the way that a moving object passes through nodes can be predicted.

Some new intelligent approaches to the second method have been proposed recently [24–26]. Anagnostopoulos et al. proposed a context model based on machine learning techniques [27]. In this model both spatial and temporal context prediction are regarded as context classification. They also proposed an adaptive mobility prediction algorithm, which addresses the problems of location context representation and trajectory prediction of moving users [28]. This algorithm adopts a spatial and temporal online clustering algorithm. Adaptive resonance theory (ART) is used for trajectory prediction. The machine learning technology is used to classify trajectories. By combining recurrent self-organizing maps and the Markov model, Han et al. proposed a trajectory-based approach [29]. This approach is effective even in ambiguous situations. However, in this approach, the training of the Markov model must be completed before prediction, and no additional modification is permitted once it is completed. Anagnostopoulos et al. treated the problem of movement prediction as a classification task and proposed a movement prediction work-flow [30]. This work-flow includes a knowledge base, which is used to compare the movement information on an object with stored information. The comparative result is used to predict the object's future location. To keep the knowledge base concise, optimal stopping theory is used in the work-flow.

The spatial and temporal parameters are considered in some models of the second method above. However, more parameters, such as speed, course, type of vessel, and others, must be considered to predict the future trajectories of vessels because the parameters are the factors that affect the result of the prediction. To solve this problem, an intelligent model is proposed in the present study. Not only the spatiotemporal parameters but also the other parameters associated with vessels can be input into the model. Although it uses more parameters than in previous practice, this model requires less human intervention. Moreover, the historical and real-time data from vessels can be utilized to predict their future trajectories.

The remainder of this paper is organized as follows: Section 3 describes the methodology of the model of trajectory prediction. Section 4 presents experiments to evaluate the performance of the model, including the results, analysis, and discussion. Section 5 summarizes the conclusions.

3. Methodology

In this section, an overview of the model of trajectory prediction is presented. The definitions below need to be introduced.

The parameters, which are used to cluster historical trajectories, are called Clustering Parameters in the model. The parameters used to classify a new vessel's cluster are called Classification Parameters. The database used to train the classifiers is called Database for Training Classifier, and the center trajectory of a cluster is called Center Trajectory.

3.1 Flow Chart of the Trajectory Prediction Model

This model consists of two main parts: historical trajectory clustering and classification of new vessels, as shown in Figure 1. The future trajectory of a new vessel can be predicted based on the cluster properties of objects belonging to the same clusters and that are dissimilar to those of objects belonging to other clusters [31–34]. Thus, the future trajectory of a vessel is equal to the Center Trajectory of its cluster. The functions of the other parts are to connect the two parts and support the model to complete the prediction. Information on vessels should be input into this model in chronological order.

3.2 Historical Trajectory Clustering

The goal of trajectory clustering is to determine the intrinsic groups of historical trajectories. Some important

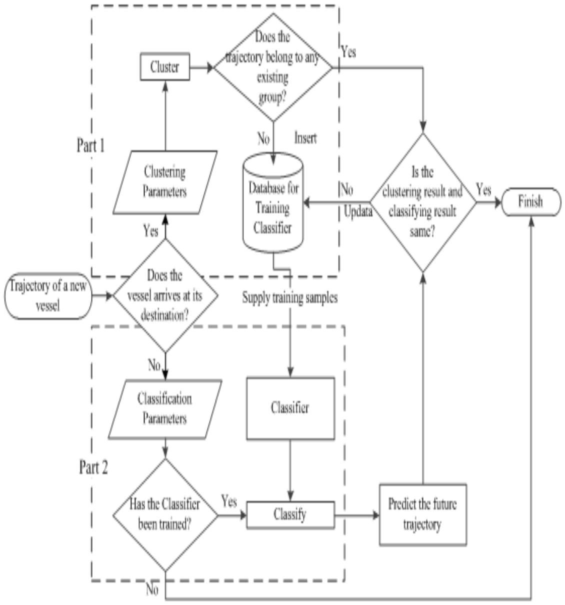

Figure 1. Flowchart of the trajectory prediction model of vessels

concepts and steps are introduced below.

First, the Clustering Parameters should be selected. The selected parameters should be those that can be achieved during the movement of a vessel or upon its arrival at its destination. Moreover, the Clustering Parameters are used to predict the trajectories of new vessels. Thus, selecting the appropriate parameters is very important.

Second, the distance between trajectories should be calculated. This distance is defined by the Clustering Parameters, which may contain different types of information on vessels. Thus, the distance algorithm must be very universal to synthesize such information.

Third, the Center Trajectory of a cluster needs to be chosen. As stated above, the samples for clustering are input to the model one by one. Thus, the clustering in this model is a dynamic process. If a new trajectory is input to the model and this trajectory is the first of a new cluster in the Database for Training Classifier, then it is used as the Center Trajectory in this study.

Finally, the distance threshold for clustering needs to be given before prediction. When a new sample is input to the model for clustering, the distance between it and other samples in the Database for Training Classifier is calculated and compared with the distance threshold. The clustering is based on the comparative results.

Let variables α_1, α_2, ... α_n stand for n Clustering Parameters, and *P* and *Q* stand for two trajectories. The difference between α_i in *P* and *Q* is

$$\Delta\alpha_i(P,Q) = \|\alpha_i(P) - \alpha_i(Q)\|, i = 1,2,\dots,n \qquad (1)$$

where $\|\alpha_i(P) - \alpha_i(Q)\|$ can be defined according to the requirements of practical applications. For example, if α_i stands for the points' location of trajectories, then $\|\alpha_i(P) - \alpha_i(Q)\|$ can be the distance between P and Q. The distance between and can be calculated by Equation. (2).

$$D(P,Q) = \sum_{i=1}^{n} K_i \frac{\Delta\alpha_i(P,Q)}{\mathrm{Max}\alpha_i} \qquad (2)$$

$$\sum_{i=1}^{n} K_i = 1 \qquad (3)$$

where $D(P,Q)$ is the distance between P and Q, K_i is the weight coefficient of α_i, and $Max\alpha_i$ is the maximum value of α_i.

Let L stand for the group label; h groups exist in the Database for Training Classifier; and the Center Trajectories of all the groups are $\{W_1, W_2, \dots W_h\}$. The corresponding labels of the Center Trajectories are $\{L(W_1), L(W_2), \dots, L(W_h)\}$ and $L(W_i) = i, i = 1,2,\dots,h$ .The group label of trajectory W' is unknown, and the Clustering Parameters of trajectory W' are known. The distances between W' and $\{W_1, W_2, \dots W_h\}$ can be calculated as $\{D(W',W_1), D(W',W_2), \dots, D(W',W_h)\}$.

$$\Delta D = \min\{D(W',W_1), D(W',W_2), \dots, D(W',W_h)\} - D_{threshold} \qquad (4)$$

Let $D_{threshold}$ stand for distance threshold for clustering. If $\Delta D \le 0$, then W' belongs to the group whose Center Trajectory is the nearest trajectory to W'.

$$L(W') = \arg\min_{1 \le i \le h}\{D(W',W_i)\}, i = 1,2,\dots,h \qquad (5)$$

If $\Delta D > 0$, then W' belongs to a new group.

$$L(W') = h + 1 \qquad (6)$$

$$W_{h+1} = W' \qquad (7)$$

$$L(W_{h+1}) = h + 1 \qquad (8)$$

W_{h+1} is inserted to the Database for Training Classifier and is the Center Trajectory of group $h+1$. The trajectories, which are not the Center Trajectories in the database, should be clustered again to update their group labels, as shown in Figure 2.

Trajectory V is not a Center Trajectory. W_i is the Center Trajectory of group i, $L(W_i) = i$. V belongs to group i and $L(V) = i$ because the nearest Center Trajectory to trajectory v is W_i before the new Center Trajectory W_{h+1} is inserted, as shown in Figure 2 (a). The group label of V should be updated after trajectory W_{h+1} is inserted, as shown in Figure 2(b).

3.3 Classification of the New Trajectory

In contrast to trajectory clustering, the function of classification is to determine the group of a new trajectory

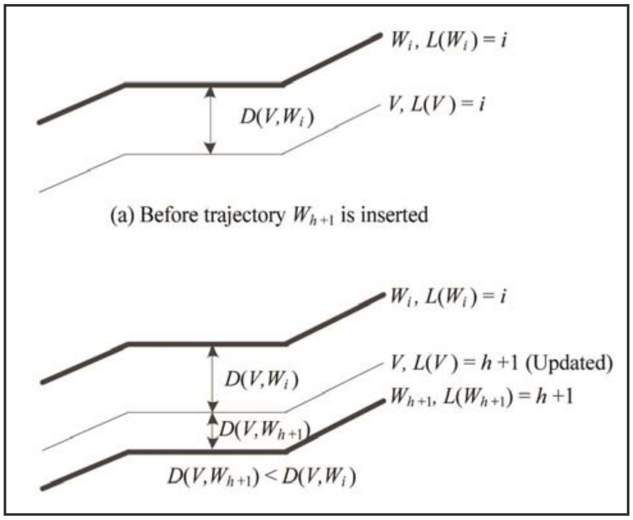

Figure 2. Updating of the trajectory's group label when a new Center Trajectory is inserted

based on the Classification Parameters. Some important concepts and steps are introduced below.

First, the Classification Parameters should be selected and are used for the prediction in this study. Thus, the parameters that can be obtained before a vessel arrives at its destination should be selected.

Second, the classifier needs to be trained. In this study, the support vector machine (SVM) is chosen as the classifier for its advantages in avoiding dimensional disaster and obtaining the global optimal solution. The Classification Parameters and group label of each trajectory are known. The SVM classifiers are trained to determine the relationship between the group labels of the historical trajectories and their Classification Parameters. Thus, the classifiers can be used to classify the cluster of a new trajectory.

Let variables $\beta_1,\beta_2,\ldots,\beta_f$ stand for the f Classification Parameters, and the s samples $\{U_1,U_2,\ldots,U_s\}$ exist in the Database for Training Classifier. The group number of the samples is h. The Center Trajectories of the groups are $\{W_1,W_2,\ldots,W_h\}$. $\{W_1,W_2,\ldots,W_h\}\subset\{U_1,U_2,\ldots,U_s\}$. Let $\beta(U_i)$ stand for the Classification Parameters of trajectory U_i. $\beta(U_i)=\{\beta_1(U_i),\beta_2(U_i),\ldots,\beta_f(U_i)\}$. The Classification Parameters of the samples are $\{\beta_j(U_i)\mid i=1,2,\ldots,s; j=1,2,\ldots,f\}$. The labels of the trajectories are $\{L(U_i)\mid i=1,2,\ldots,s\}$.

$$\begin{bmatrix} \beta_1(U_1) & \beta_2(U_1) & \cdots & \beta_f(U_1) & L(U_1) \\ \beta_1(U_2) & \beta_2(U_2) & \cdots & \beta_f(U_2) & L(U_2) \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ \beta_1(U_s) & \beta_2(U_s) & \cdots & \beta_f(U_s) & L(U_s) \end{bmatrix} \quad (9)$$

The SVM classifier is a binary classifier; thus, every two groups can be used to train one classifier. To classify all of the groups, any combination of two groups from the samples must be selected. Based on the combination formula, the number of SVM classifiers can be calculated.

$$C_h^2=\frac{h(h-1)}{2!} \quad (10)$$

Let $SVMC(i,j)$ stand for the SVM classifier of groups i and j, which is equivalent to $SVMC(j,i)$. The classifiers are

$$\begin{bmatrix} SVMC(1,2) & \cdots & SVMC(1,h) \\ \vdots & \ddots & \vdots \\ Null & \cdots & SVMC(h-1,h) \end{bmatrix} \quad (11)$$

Although SVM is a binary classifier, many methods are available to solve the multiple classification problems; examples include one against all, one against one with voting, one against one with eliminating, and other methods. In this research, the one against one with voting method is used because it can calculate the possibility of a vessel belonging to a group. This is also expected in some prediction applications.

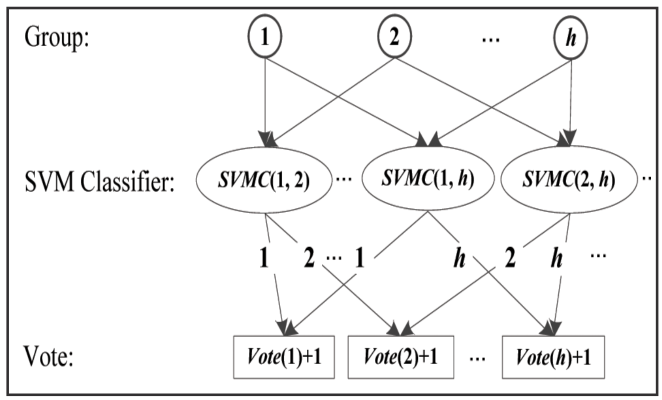

Figure 3. One against one with voting method

As shown in Figure 3, the votes of the groups are $\{Vote(i)\mid i=1,2,\ldots,h\}$. Before the classification, the vote of each group is 0. For example, let $SVMC(1,2)$ classify the group of a new trajectory. If it belongs to group 1, then $Vote(1)+1$; otherwise, $Vote(2)+1$.

After the voting, the maximum vote of any group is no larger than $s+1$. The possibility of a trajectory belonging to a group can be calculated by Equation. (12).

$$Pb(i)=\frac{Vote(i)}{h-1}, i=1,2,\ldots,h \quad (12)$$

where $Pb(i)$ is the possibility of a trajectory belonging to group i. The Pb is sorted in descending order, and the groups of top r are selected as candidates. The Center Trajectories of the candidates are equivalent to the future trajectory in this study. Thus, the trajectory is predicted. When $r=1$, this method deteriorates into the traditional one against one voting method.

When a vessel arrives at its destination, the real group that it belongs to can be calculated based on the Clustering Parameters. By comparing the candidate groups with the real group, the accuracy of the prediction can be evaluated.

4. Analysis of Results and Discussion

In this section, the trajectories of vessels are taken as examples, and the efficiency of the model is tested. The total number of trajectories is 2862. The information on the trajectories is input to this model in chronological order to simulate the real-time situation.

4.1 Trajectory Clustering Testing

Let α_1 stand for the location coordinate of each point on a trajectory, and α_2 stand for the location coordinate of the destination point on a trajectory. $\Delta\alpha_1$ is the average distance between the corresponding points on two trajectories, and $\Delta\alpha_2$ is the distance between the destinations of two vessels. Let $Max\alpha_1$ and $Max\alpha_2$ stand for the maximum distance between two points on the area where the vessels sail across. Let K_1 and K_2 be the weight coefficients of $\Delta\alpha_1$ and $\Delta\alpha_2$, $K_1 = K_2 = 0.5$. The distance between the trajectories of two vessels is

$$D = \sum_{i=1}^{2} K_i \frac{\Delta\alpha_i}{\text{Max}\alpha_i} \tag{13}$$

The value of D ranges from 0 to 1; thus, the threshold of D for clustering is $D_{threshold} \in [0,1]$. Figure 4 shows the changes in the number of groups, when $D_{threshold}$ is 0.04, 0.06, 0.08, and 0.10.

Figure 4 shows that the number of groups also increases along with the growth of the number of input trajectories; however, the rate of increase diminishes. By inference, when the number of input trajectories is sufficiently large, the number of groups increases very slowly. The groups can be kept concise with limited variance, and the Center Trajectories still include all types of the distribution of trajectories. Thus, this model is suitable for big data problems.

$D_{threshold}$ can also influence the number of groups, except for the number of input trajectories. The larger $D_{threshold}$ is, the less the number of groups is. When the trajectory of a vessel belongs to a group and the group's Center Trajectory is known, the future trajectory of the vessel can be predicted. If the prediction is right, the distance between the Center Trajectory and its real trajectory is no larger than. $D_{threshold}$ Thus, when $D_{threshold}$ becomes large, the precision of the prediction drops. As such, the value of $D_{threshold}$ should be determined by the precision request of the application.

Figure 5 shows the distribution of all the Center

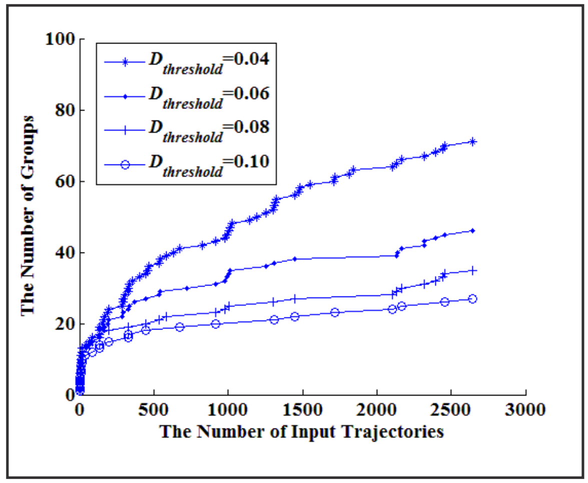

Figure 4. Number of groups when $D_{threshold}$ is 0.04, 0.06, 0.08, and 0.10

Trajectories when $D_{threshold}$ is 0.04, 0.06, 0.08, and 0.10. Although the number of groups or number of Center Trajectories becomes less when $D_{threshold}$ becomes larger, the Center Trajectories can reflect the distribution of the trajectories.

4.2 Trajectory Classification Testing

Let β_1 stand for the vessel's ID number, β_2 stand for the location coordinate of the origin point, and β_3 stand for the time at which the vessel is on its origin point. In this test, the radial basis function (RBF) is chosen as the kernel function of SVM. N_{all} is the total number of trajectories that are input to the model. N_{right} is the number of records of correct prediction. The prediction accuracy is

$$Pr = \frac{N_{right}}{N_{all}} \tag{14}$$

At the beginning, the records of several vessels are input to the model, and no sufficient groups exist to train the SVM classifiers. Thus, the new trajectories cannot be predicted and are recorded as prediction errors.

Let $D_{threshold} = 0.10$, Figure 6 shows the curves of the prediction accuracy, along with the number of trajectories that are input to the model when r is 1, 2, 5, and 10.

Figure 6 shows that Pr becomes large along with the growth of the number of input trajectories. This reflects that the model is "*learning*" to correct its prediction accuracy using the input information. When the value of Pr nearly reaches 1, the increase in its speed slows down, which means that the model has nearly "*mustered*" the related relationship between the initial status parameters and group labels of the vessels. The distribution of the trajectories is *"known"* by the model. Thus, the model then rarely "*learns*" "new knowledge" from the input trajectories, when the number of input trajectories is sufficiently large. If the distribution of the trajectories changes for some reason, then the prediction

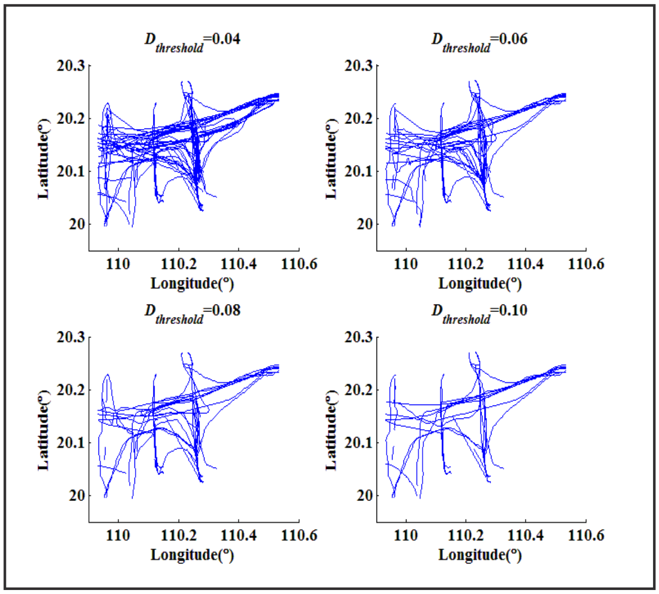

Figure 5. Distribution of all the groups' Center Trajectories when $D_{thershold}$ = 0.10

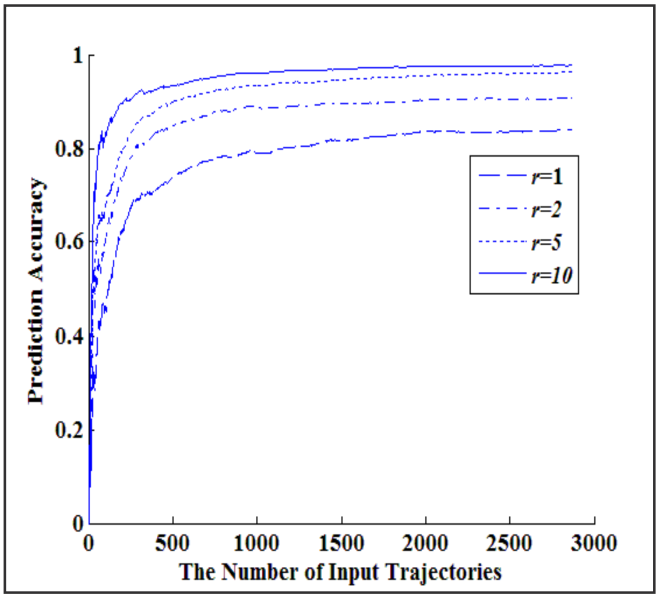

Figure 6. Prediction accuracy when $D_{threshold}$ is 0.01 and r is 1, 2, 5, and 10

accuracy may drop, and the model should "*learn*" "*new knowledge*" again to adapt to the change.

When all of the trajectories are input to the model, Pr = 0.8399 with r = 1, Pr = 0.9081 with r = 2, Pr = 0.9626 with r = 5, and Pr = 0.9769 with r = 10. The prediction accuracy becomes higher when the number of candidates becomes larger. Although more candidates may lead to multiple results and complicate the prediction results, more candidates are desirable in some applications.

Let r = 5, Figure 7 shows the curves of the prediction accuracy along with the number of trajectories that are input to the model when $D_{thershold}$ is 0.04, 0.06, 0.08, and 0.10.

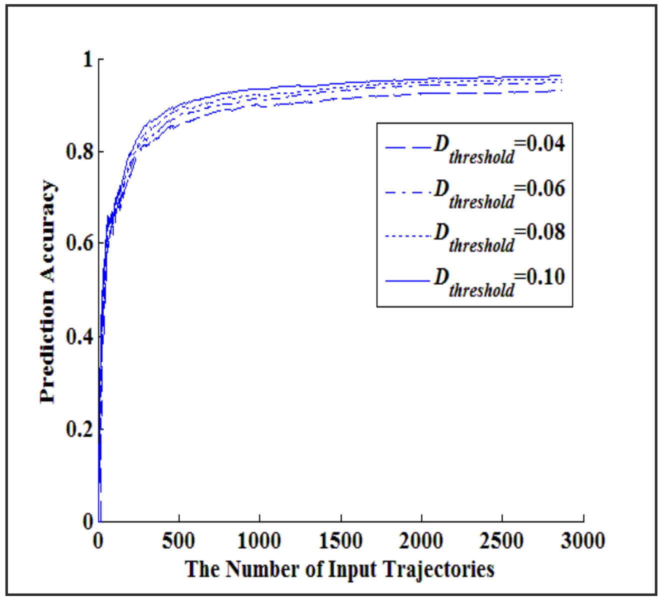

Figure 7. Prediction accuracy when r is 5 and $D_{threshold}$ is 0.04, 0.06, 0.08, and 0.10

As shown in Figure 7, when all of the trajectories are input to the model, Pr = 0.9626 with $D_{thershold}$ = 0.10, Pr = 0.9558 with $D_{thershold}$ = 0.08, Pr = 0.9486 with $D_{thershold}$ = 0.06, and Pr = 0.9308 Pr with $D_{thershorld}$ = 0.04. The prediction accuracy becomes lower when the value of $D_{thershold}$ becomes smaller. When $D_{thershold}$ becomes smaller, the distance between two adjacent Center Trajectories becomes smaller. Thus, it becomes more difficult for classifiers to make a correct judgment. From the point of view of prediction, when the prediction precision becomes higher, the prediction accuracy becomes lower. This is consistent with the actual situation.

4.3 Example of Prediction Results

Let $D_{threshold}$ = 0.04 and r = 4, Figure 8 describes a new trajectory V', and the four Center Trajectories W_1'', W_2'', W_3'', W_4''. V' is the trajectories that must be predicted. $Pb(W_i'')$ stands for the possibility of V' belonging to group i, and $i = 1,2,3,4$. The experimental results are $Pb(W_1'')$=1, $Pb(W_2'')$=0.85714, $Pb(W_3'')$=0.78571, and $Pb(W_4'')$=0.71429.

As shown in Figure 8, trajectory W_1'' is the most similar trajectory to V'. The information on W_1'' can be used to predict trajectory V'. The classifying result, $Pb(W_1'')$ = max $\{Pb(W_i'')| \ i = 1,2,3,4\}$), also shows that trajectory V' belongs to the group whose Center Trajectory is W_1''. Thus, this model for trajectory prediction is practicable.

5. Conclusions

An intelligent model is proposed in this study to predict the future trajectories of vessels. A new flowchart is

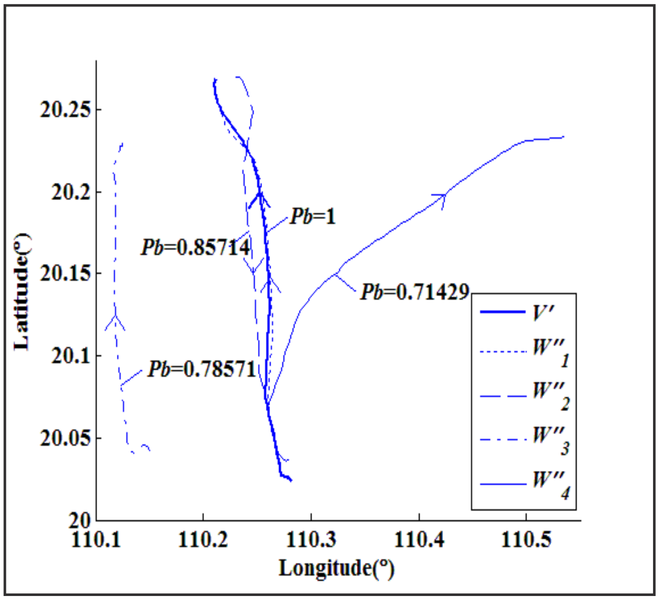

Figure 8. Example of a prediction result when $D_{thershold}$ is 0.04 and r is 5

designed in this model based on data mining and machine learning methods. The framework of the flowchart makes the model more versatile than it previously was because all the information related to the vessels can be input to the model. The experimental results show that the model can automatically adapt to changes in the traffic data and reflect the evolution of the distribution of the trajectories of vessels. This is very important for the study of traffic flow and traffic planning. Generally, traffic flow changes slowly along with changes in the environment and the development of transportation technology. The clustering and classification algorithms in this model can solve the prediction problem under such change. The model can address real-time traffic data and provide accurate predictions of real-time trajectories. The prediction results can supply data support for traffic management, accident detection, and avoidance of automatic collision and therefore promote the development of maritime intelligent traffic systems. Further research based on this method is required, especially for abnormal detection and traffic flow simulation.

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