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Intelligent Trip Modeling on Ramps using Ramp Classification and Knowledge Base

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***Abstract*—Speed profile prediction on ramps is a challenging problem because speed changes on ramps involve complicated lane maneuvering and frequent acceleration or deceleration depending on geometry of the ramp and traffic volumes. Ramps can be categorized into three groups based on their interconnection of freeway: freeway entering ramps, freeway exit ramps, and inter freeway ramps. However, different geographical shapes of ramps within the same category cause different speed profile distributions. To predict speed profile on any ramp types, we proposed an Intelligent Trip Modeling on Ramp (ITMR) System that consists of a ramp classification method based on the decision tree and speed profile prediction neural networks. The proposed ITMR takes inputs from geographical data on the route and also the personal driving pattern extracted from the knowledge base built with the individual historical driving data. Experimental results show that the proposed system learned dynamic ramp speed changes very well to provide accurate prediction results on multiple freeway entering ramps, exit ramps and inter freeway ramps.**

Keywords— speed prediction; trip modeling; traffic model; ramp;

I. INTRODUCTION

Recently, Advanced Traffic Information System (ATIS) has drawn lots of attention due to the explosive sensor technology innovations and vast amount of real time and historical traffic information available. ATIS can support a driver by providing useful predictive traffic information using combined traffic information [1].

Trip modeling for speed profile is to predict a spatial distribution of traveling speed along a route. In ATIS the accurately predicted traffic information can be used to reduce the uncertainty of the future traffic states, improve traffic mobility, and provide the driver with a realistic estimation of travel times, expected delays and alternative routes to the destinations. Our and other's research showed that an accurately predicted vehicle speed profile of an intended route is important to achieve optimal fuel economy in a hybrid electrical vehicle (HEV) [1-5], and estimate distance-to-go in Electric Vehicle (EV) [6].

Ramps provide interfaces between different traffic facilities through speed-change lanes. Speed-change lanes allow vehicles to increase speed or decrease speed for safe and smooth transition. The speed-change lane for on-ramp (freeway entering ramp) is an acceleration lane, while the speed-change lane on off-ramp (freeway exit ramp) is a deceleration lane [7]. Although ramps are significantly shorter in length compared with other traffic facilities, its speed profile usually changes dramatically. Trip modeling of speed profile on ramps has lots of potential in assessing the ramp geometric design, operations, safety of a roadway facility, and vehicle power management [8-9].

Speed profile prediction on ramps is a challenging problem because speed changes on ramps involve complicated lane maneuvering, frequent acceleration or deceleration depending on geometry of each ramp, number of lanes, and traffic volumes. Ramps can be categorized into three groups based on their interconnection of freeway: freeway entering ramps, freeway exit ramps, and inter freeway ramps. However even for ramps in the same category, different geographical shapes of ramps cause different speed profile distributions. Ramps also show significant speed pattern variations due the fact that drivers often make a transition through a ramp to different traffic facilities.

For the last decade, research in traffic information prediction has been very active. The techniques can be broadly categorized into two groups: model based and data-driven methods [10]. Model based approaches predict future traffic states on the route of interest based on theoretical models [11]. In general, model based approaches need expertise for design and maintenance of the traffic model, and extensive calibration of traffic model parameters on a site-by-site basis [10]. On the other hand, data driven traffic modeling approaches relate observed traffic conditions with current and past traffic data without using explicit physical traffic models. Data driven approaches are fast to develop since they do not require extensive expertise in traffic prediction modeling [6], [11]–[14]. However, most of this work has been focused on freeways, whereas little work focuses on traffic information predictions on ramps.

Recently, Huang et al. [4] proposed modeling speed profiles on freeway exit ramps using support vector regression. They collected data using radar guns at 400 ft intervals on 24 freeway exit ramps and speed data were collected 10 times for each collection point. But the proposed speed profile model has unsatisfying performances with 11.50% error over real measured data.

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Even though ramps are already classified into the three categories mentioned above, the ramps within each category have different physical shapes that result in different speed profiles. Another challenging issue in speed profile predictions on ramps is lack of dynamic traffic data on ramps. In general, traffic sensor data on ramp are not available. Using only geometric data and traffic sensor data on the nearby freeway is not enough to generate reliable speed profiles. To make the prediction system robust, we build a Knowledge Base (KB) using the individual driving historical data on the known routes. The KB provides individual driving statistics based on geographical characteristics. The information extracted from the KB can be utilized for any new route to improve the speed prediction performances.

In this paper, we present an Intelligent Trip Modeling on Ramp (ITMR) System that extracts information from the KB based on ramp classification and predicts a speed profile on any ramp at the given trip starting time. ITMR uses ramp geometry information, traffic data on the nearby freeway and statistics extracted from the KB. This paper is organized as follows; In Section II, we present ramp classification and build the Knowledge Base using individual historical driving data. Ramp speed profile prediction Neural Networks (NNs) are explained in detail in Section III. The proposed ITMR is then evaluated with real driving recorded data in Section IV. Finally, the conclusion is presented in Section V.

II. RAMP CLASSIFICATION AND KNOWLEDGE BASE

Traffic information predictions such as speed, flow, and travel time are complex non-linear spatial-temporal problems for which the dynamics in free-flowing and congested conditions are different. Artificial Neural Networks (ANN) have been applied successfully in the prediction of traffic information such as speed, flow, and travel time [4], [6], [15-16]. The ANN based approaches [12-13] are able to learn complicated non-linear relationship between input features and output patterns. The ANN based approaches are relatively less sensitive to erroneous or missing data and they are independent of the particular geometry of prediction location.

The objective of this research is to predict individual driving speed profiles on ramps at the trip starting time. The prediction relies on the geographical information of the ramps, TMC traffic information provided by ATIS, and statistical information available from the KB that was built using available historical driving data on any ramp routes. To predict the individual driving speed at each traveling point along the selected ramp route before the trip starts, we build Ramp Speed Profile Prediction (RSPP) NN systems.

A. *Traveling Points on Ramp*

According to ATIS (e.g. in our case provided by Here or former Nokia/Navteq), geographical information data are organized hierarchically with three concepts: *Traffic Message Channel (TMC) sections*, *links*, and *shape points* as shown in Fig.1. To generate more precise speed prediction at finer resolution than shape point and link, we defined *traveling points* based on speed limit and free flow speed on ramps such that a shape point contains several traveling points. Using traveling points, the ramp R can be defined as a series of traveling points x_i, i=1,..., M where x_i is defined by its longitude and latitude and M is the index of the last traveling point on the ramp and the longer ramps have the larger M value: $R = \{x_1, x_2, ..., x_M \mid x_i = (longitue_i, latitude_i)\}$.

B. *Ramp Classification*

Ramps have various different physical shapes even within the same ramp type (e.g. freeway entering ramp). Fig. 2 shows three freeway entering ramps and set of corresponding speed profiles which were recorded by individual drivers using GPS. As shown in Fig. 2, different ramp shapes causes the different ramp speed profiles even though they are all freeway entering ramps.

Ramp classification is an essential procedure to group the ramps with similar shapes. The purpose of ramp classification is to improve speed profile prediction performance on ramps by grouping similar physical shapes of ramps. With the current ATIS, available information for the ramp classification is geometric information only. If the historical individual driving data on the ramp exists, the historical data is useful for the ramp classification by grouping ramps with similar historical speed profiles. But historical individual driving data is not available for every ramp. Also, this ramp classification needs to be done quickly so ITMR system is able to predict the speed profile in real time. Considering the available data limitation and processing timing constraint, a hierarchical decision tree is a good candidate for the ramp classification, which is a rule-based classification method with satisfactory performances and quick response time.

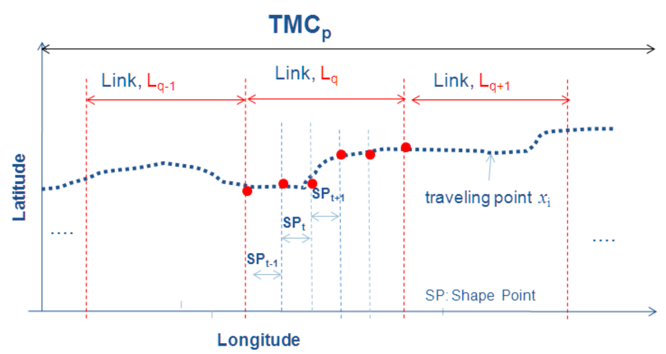


Fig.1. Relationship between TMC, link, shape points and traveling points.

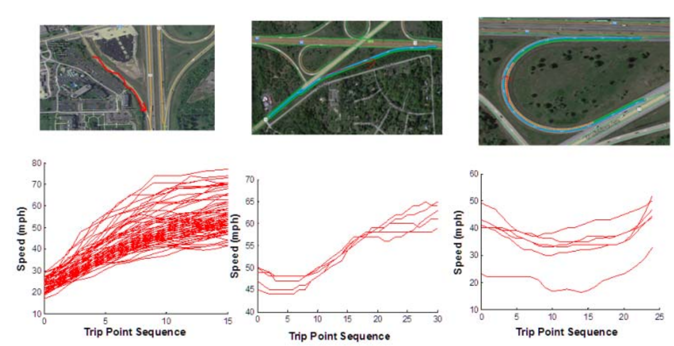


Fig. 2. Different entering ramp shapes and corresponding speed profiles.

Fig. 3 presents the proposed decision tree for the ramp classification. In the ramp classification decision tree, the root node is a ramp type, i.e. freeway entering ramp, freeway exit ramp, and inter freeway ramp. Geographical features such as speed limit, curvature distribution mode, and the location of large curvature on the ramp are used to split the decision tree after the root layer.

First, the decision tree is splitting based on the speed limit. Then, the decision three is divided into the next layer using the curvature distribution mode on the ramp. The curvature distribution mode represents the most frequent curvature range on the ramp. Fig. 4 shows three different curvature distribution modes in three different ramp shapes. Based on the analysis of curvature distribution on the ramps presented in Fig. 5, we defined four bins with 2.5° curvature range from 0° to 10° such that Bin1 = [0°, 2.5°], Bin2= (2.5°, 5°], Bin3= (5°, 7.5°] and Bin4= (7.5°, 10°]. Then the fifth bin is set to the large curvature range 10° to 90° (i.e. Bin5= (10°, 90°]) because curvatures in this range do not occur frequently.

For each traveling point x_i, the curvature $\Theta(x_i)$, is calculated as follow:

$$\theta(\mathrm{xi}) = \arccos\left(\frac{\overrightarrow{x_{i-1}x_i}\cdot\overrightarrow{x_i x_{i+1}}}{\|\overrightarrow{x_{i-1}x_i}\|\|\overrightarrow{x_i x_{i+1}}\|}\right) \tag{1}$$

where $\overrightarrow{x_a x_b}$ is an Euclidean vector from x_a to x_b and $\cdot$ is the dot product. To determine the curvature distribution mode, every traveling point on the ramp votes for its corresponding curvature bin. Based on the curvature of the traveling point x_i on the ramp, $\Theta(x_i)$, the corresponding bin has increased its frequency value by 1. Among 5 bins, the bin with the most frequencies is selected as the curvature distribution mode.

After the decision tree for the ramp classification is split according to the curvature distribution mode, the tree is divided into one more layer using the large curvature location on the ramp because drivers tend to decrease the speeds at the locations of large curvature on the ramps. Thus, a ramp with the large curvature point at the beginning will have a different speed profile than a ramp with the large curvature point at the end. We defined that the curvature is large if the curvature on the traveling point x_i, $\Theta(x_i)$, is greater than threshold (we used 20°). Four different categories are defined based on the large curvature location: 1) no large curvature 2) large curvature at the first third part of the ramp, 3) large curvature points at the rest of two third of the ramp, 4) both portion has large curvature points. Based on our observation, driving patterns appear to be different at the first third part of the ramp from the last two third of the ramp. For example some ramps have different curvatures at the beginning than the rest of ramps.

Fig. 6 presents two cases when the large curvature exists at end of the ramp and at the beginning of the ramp. The corresponding speed profile shows that the speeds are decreased when the curvature is large. Fig. 7 presents examples of the ramp classification results based on the decision tree using speed limit, curvature distribution mode, and large curvature location on the ramp. Two circular shape freeway entering ramps in Figure 7a are classified as the same group and two rather straight ramps in Figure 7b are grouped into the same category. The decision tree is tested with 40 different ramps (16 entering ramps, 13 exit ramps, and 11 inter freeway ramps) and it classifies into 24 different ramp groups using the decision tree mentioned above

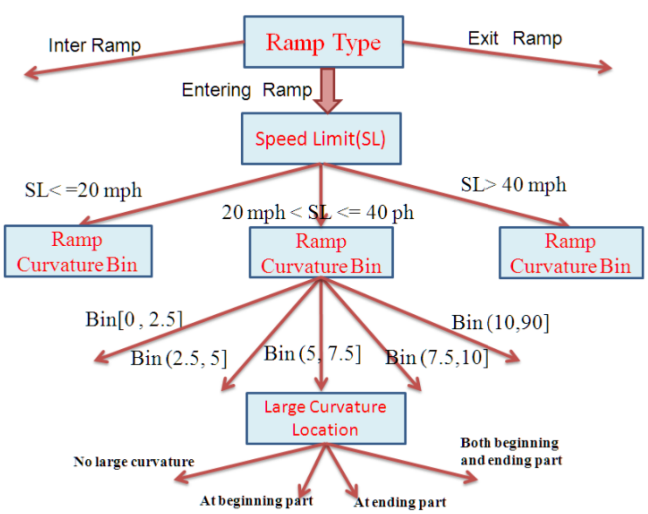


Fig. 3. Ramp classification decision tree based on speed limit and curvature distributions.

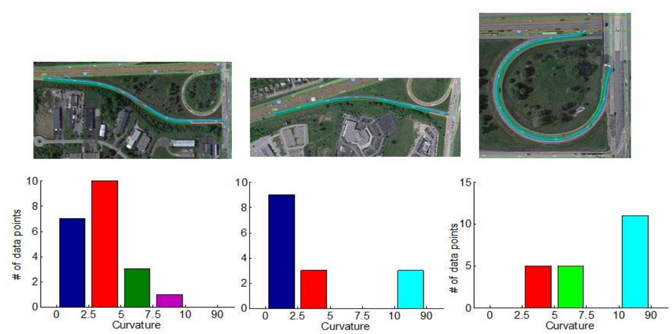


Fig. 4. Curvature distribution modes in different ramp shapes.

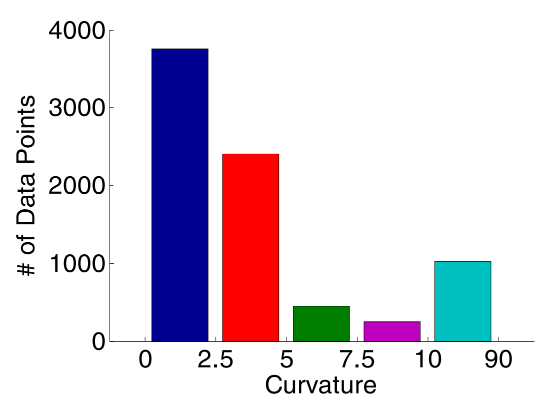


Fig. 5. Example of histogram of curvature on freeway entering ramps.

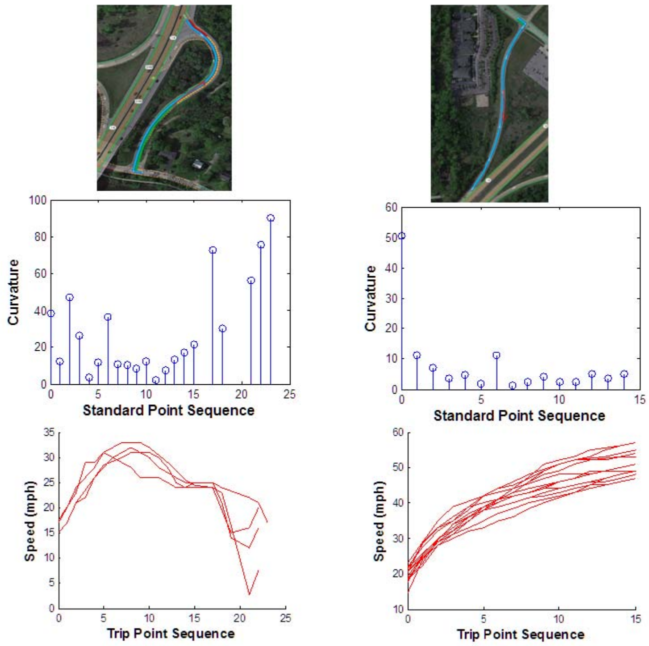
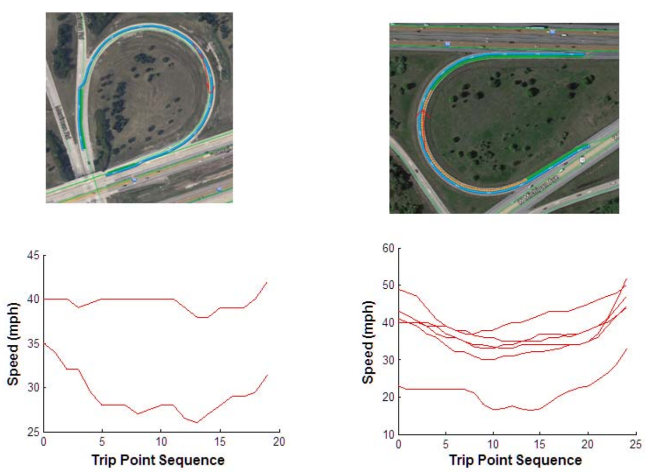
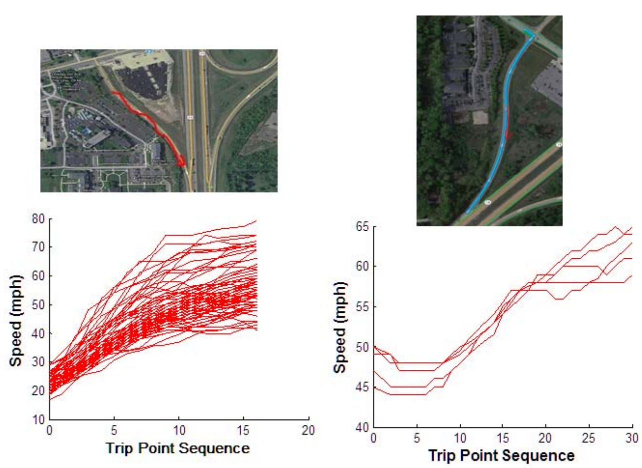


Fig 6.Example of large curvature locations and speed profiles.



(a) Entering Ramp classification: group 1



(b) Entering Ramp classification: group 2

Fig. 7. Examples of entering ramp classification by the decision tree.

C. Building the Knowledge Base and Extraction of Statistics based on Matching

Historical individual driving data on a route can contain useful information for speed profile prediction. Based on the correlation analysis, a driver's speed profile has a very high correlation with the driver's own historical driving statistics. However, these historical individual driving data are often not available for every route, therefore, when the speed profile prediction is needed on a new route, the historical driving statistics may not be available. In order to deal with this situation, we build a Knowledge Base (KB) that contains the individual driving statistics with respect to road geographical features. The ramp KB can be built using an incremental learning process. The KB can be updated whenever new driving data are available without referring to the previous training data.

When a speed profile prediction on a new route is requested and there are no historical driving data available, we use the following matching algorithm to extract the historical driving statistics from the best matching traveling points in the ramp KB.

Step I. Find the ramp category *K* for the new ramp using the decision tree (presented in Chapter II-*B*) based on geographical information such as speed limit, the curvature distribution mode, and the large curvature location.

Step II. For every traveling point x_i on the new ramp where i=1,...,M and M is the last traveling point on the new ramp,

1) Find the set of traveling points among the ramps with the same category *K*. For the simplicity, those traveling points are denoted as $\Omega=\{k_1,...,k_N\}$.

2) Find the best matching point in $\Omega=\{k_1,...,k_N\}$ with x_i on the new ramp. This traveling point to point matching process is based on two features, the curvature and the distance from the beginning of the ramp. The best matching traveling point in $\Omega=\{k_1,...,k_N\}$ is found with the shortest Euclidean distance as defined below:

$$\mathrm{Min}_{k_j \in \Omega}\,(\sqrt{\left(\theta(x_i)-\theta(k_j)\right)^2 + D(x_i)-D(k_j))^2}) \qquad (2)$$

where $D(p)$ is the distance from the beginning of the ramp to the location p.

For example, Fig. 8 presents the best matching traveling point in the ramp category *K* with the traveling point x_2 (red circle) on the new route. To find the best matching traveling point in the KB category K, the Euclidean distances between x_2 on the new route and all point $k_j \in \Omega$ in the KB category K, are calculated. Then, the traveling point with the minimum Euclidean distance is selected as the best matching traveling point (green color) in the KB category K.

III. RAMP SPEED PROFILE PREDICTION NEURAL NETWOKR

The objective of this research is to predict the speed profile on any ramp. To accomplish the objective, we developed Ramp Speed Profile Prediction Neural Networks (RSPPNN)

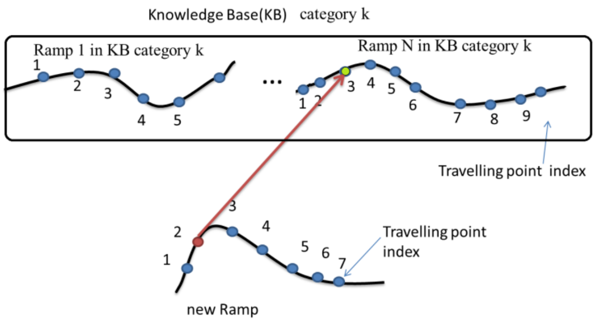


Fig.8. Matching the new ramp with known ramps in knowledge base.

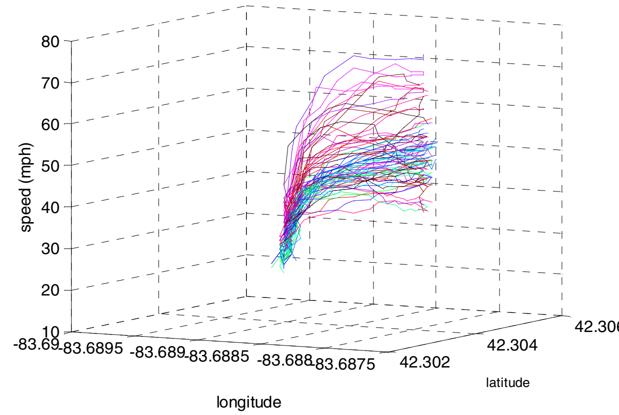


Fig.9. Recorded Speed profiles on a selected freeway entering ramp.

system that predicts the driving speed profile along the selected ramp route before the trip starts. Traffic information predictions such as speed, flow, and travel time are complex non-linear spatial-temporal problems for which the dynamics in free-flowing or congested conditions are different. The learning capabilities of neural networks make them a suitable approach for solving the complicated non-linear traffic prediction problem. The NN based traffic prediction system requires time intensive training to learn from the traffic training data and also the performance of NN based the traffic prediction system is very much dependent on the design of its input features and its architecture. Analysis of the features available to choose highly correlated input features with the output is an important step when developing a reliable speed prediction system.

A. Feature Selection based on Correlation Analysis

All the geographical information on ramps is acquired through an ATIS (in our case provided by Here or former Nokia/Navteq) and the available information includes latitude, longitude, altitude, number of lanes, curvature, speed limit, etc. The individual driving data on the selected ramps were collected by two different vehicles equipped with data loggers and a total of 720 trips on 40 different selected ramps were recorded. Fig. 9 displays speed profiles recorded on different days on a freeway entering ramp at the intersection between the local Plymouth Road and freeway I-94 in Ann Arbor, Michigan, U.S.A. In Fig. 9, the speed profile is represented in a three-dimensional plot where x is longitude, y is latitude and z is the actual recorded speed in miles per hour (mph). Using individual driving historical data on ramps, a KB was built that contains average historical speed, standard deviation of historical speed, and the maximum and minimum historical speed at each traveling point on the ramp. Since the vehicle speed on the ramp is quite related with the location on the ramp, two more features are defined by us. First, the distance from the beginning of the ramp to the traveling point x_i, $D(\boldsymbol{x_i})$ is calculated. Secondly, the distance from x_i to the nearest point where the curvature is larger than 20° is calculated and denoted as $\boldsymbol{D_{large}}(\boldsymbol{x_i})$.

To find effective input features to the RSPPNN system among all available geographical & historical statistics features, Pearson correlation analysis is applied. Pearson correlation measures how well the variables are related. We applied this analysis between recorded true vehicle speeds and each of the available features. TABLE I presents the top 6 highest correlated features with the true recorded speed on various ramps, where $\mu(x_i)$ is the average historical speed, $\sigma(x_i)$ is standard deviation of historical speed, $\max(x_i)$ is maximum historical speed, and $\min(x_i)$ is minimum historical speed at the traveling point x_i. For the freeway entering ramp and the exit ramp, the average historical speed $\mu(x_i)$ has the highest correlation with the true vehicle speed. For the inter freeway ramp, the location index (i.e. traveling point x_i) has the highest correlation with the true vehicle speed. Based on this analysis, the top 6 highly correlated features were selected as inputs to the RSPPNN system.

B. Architecture of Ramp Speed Profile Prediction NN

The RSPPNN is built with the multi-layer perceptron (MLP) type neural network which consists of three layers with one single output which is the predicted speed. A back-propagation algorithm is used for all NN training, a log sigmoid transfer function is used for the hidden layer, and a pure linear transfer function is used for the output layer. The hidden layers of these neural networks vary from 5 to 50 hidden nodes. The number of hidden nodes for each neural network hidden layer is determined using the following training process; for each possible number of hidden nodes we apply 3-fold cross validation to train and evaluate the system. The number of hidden nodes that gave the best validation results is chosen for the neural network. According to the experiments results, the best hidden node number are 10, 15, and 10 for entering ramp NN, inter freeway ramp NN, and exit ramp NN respectively.

Based on the feature selection analysis in Section III-*A*, the RSPPNN is designed to take the three different types of inputs: geographical inputs, individual historical inputs, and the dynamic traffic TMC data which is the traffic sensor data on the freeway where the ramp merges and denoted as $\boldsymbol{V_{TMC}}$. For the inter freeway ramp, TMC data near the beginning of the ramp is used because two TMC data are available on the inter freeway ramp (i.e. near the beginning and the ending of the ramp). Three geographical input features are used: 1) the location index at x_i, $LocationIndex(\boldsymbol{x_i})$, 2) the distance from the beginning of the ramp to the traveling point x_i, $D(\boldsymbol{x_i})$, and 3) the distance from x_i to the nearest point where the curvature is larger than 20°, $\boldsymbol{D_{large}(x_i)}$. The individual historical driving features used as inputs to RSPPNN system are 1) the average speed of historical driving data at x_i, $\mu(x_i)$, 2) standard deviation of historical driving speed at x_i, $\sigma(x_i)$, 3) the maximum historical driving speed at x_i, $\max(x_i)$, and 4) the minimum historical driving speed at x_i, $\min(x_i)$. The output of the RSPPNN is the predicted speed at the location x_i. Fig. 10 presents the architecture of the RSPPNN.

IV. Implementation and Experiment Result

As described earlier in the paper, our Intelligent Trip Modeling on Ramp (ITMR) system consists of a ramp classification decision tree, knowledge base built with individual historical driving data, and speed profile prediction neural networks, RSPPNN. The overall architecture of the ITMR system is presented in Fig. 11. When a speed profile is predicted on a new route, the ITMR system first classifies the ramp category based on geographical information as explained in Section III-*B*. Then, a matching process is performed to extract the historical statistics at the best matching traveling points from ramps with the same category in KB. Finally, input features defined in Fig. 10 are generated and fed into the RSPPNN system. The output of the system is the predicted speed profile on the ramp.

TABLE I. Pearson Correlation Analysis Results

Entering Ramp		Inter Ramp		Exit Ramp	
Symbol	***CR****	***Symbol***	***CR****	***Symbol***	***CR****
$\boldsymbol{\mu(x_i)}$	0.9257	$\boldsymbol{x_i}$	0.5961	$\boldsymbol{\mu(x_i)}$	0.9128
$\boldsymbol{x_i}$	0.8759	$\boldsymbol{D(x_i)}$	0.5940	$\boldsymbol{\min(x_i)}$	0.8719
$\boldsymbol{D(x_i)}$	0.8604	$\boldsymbol{D_{large}(x_i)}$	0.4716	$\boldsymbol{x_i}$	0.8614
$\boldsymbol{D_{large}(x_i)}$	0.8452	$\boldsymbol{\max(x_i)}$	0.4639	$\boldsymbol{\max(x_i)}$	0.8419
$\boldsymbol{\min(x_i)}$	0.7641	$\boldsymbol{\min(x_i)}$	0.4622	$\boldsymbol{D(x_i)}$	0.8390
$\boldsymbol{\max(x_i)}$	0.7345	$\boldsymbol{\sigma(x_i)}$	0.4205	$\boldsymbol{D_{large}(x_i)}$	0.8205

(CR : Correlation Value)*

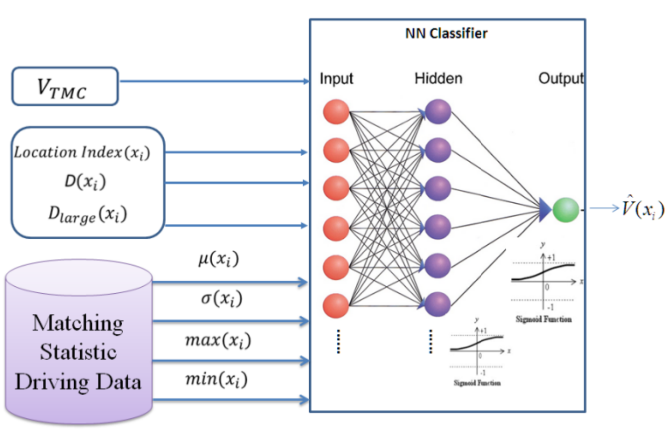


Fig.10. The architecture of RSPPNN.

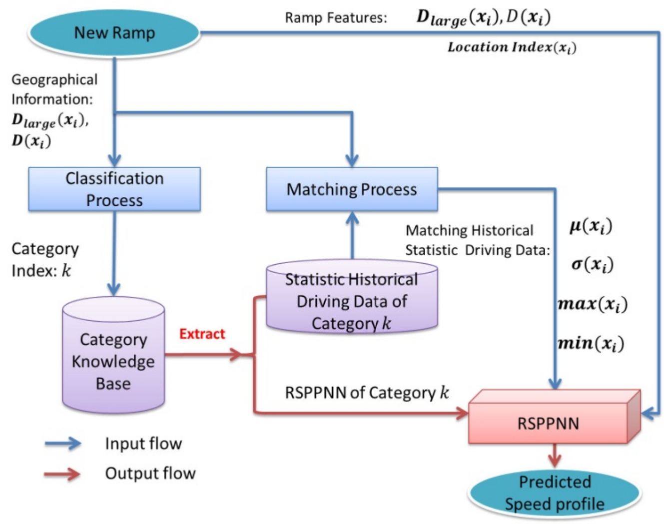


Fig.11. The architecture of an Intelligent Trip Modeling on Ramp (ITMR) System.

In order to evaluate ITMR system, real driving trips on various ramps are recorded by multiple drivers at Ford Motor Company. The real driving data set contains 720 trips on 40 different ramps (16 entering ramps, 11 inter freeway ramps, and 13 exiting ramps). The evaluation of ITMR system is performed in cross region validation. For an example, if two ramps, Ramp #1 and Ramp #10, are in the same category, both of the ramps are tested with the RSPPNN trained on the other ramp. So the speed profile prediction on Ramp #10 uses the system trained with Ramp #1 and vice versa.

The ITMR system prediction performance is measured using mean absolute error (MAE). Mathematically, a true recorded speed profile, $\vec{V}$ for the give route R is a series of speeds v_i recorded at the traveling points x_i,

$$\vec{V} \triangleq \{v_1, v_2, \dots, v_m\} \tag{3}$$

The predicted speed profile, $\vec{U}$ for the given route R is a series of speeds $\hat{u}_i$ predicted at the points x_i.

$$\vec{U} \triangleq \{\hat{u}_1, \hat{u}_2, \dots, \hat{u}_m\} \tag{4}$$

Thus,

$$Prediction\ MAE = \frac{\sum_{i=1}^{m} |\hat{u}_i - v_i|}{m}. \tag{5}$$

Fig. 12 presents an example of the predicted speed profile by ITMR system (blue plot) on Miller Rd to US-14 in Ann Arbor, Michigan, U.S.A. The true recorded speed profile is superimposed with red color in Fig. 12. The MAE of the proposed ITMR system in this case is 1.921 mph. TABLE II shows the performance of ITMR system on freeway entering ramps. Total 16 freeway entering ramps are evaluated using 337 trips. The average performance of ITMR on freeway entering ramps is 6.9782 mph. For the comparison, the performance of the system without KB is calculated as a baseline. The baseline system is implemented exactly the same way with the ITMR system except that it only takes inputs of dynamic traffic TMC data and the geographical data to RSPPNN. In general, ITMR system improves the performance 14% over the system without KB. The performance of Ramp 8 and Ramp 11 are not good because of lack of the training data (these ramps belong to the same group but Ramp #11 only has one trip, and Ramp #8 only has 2 trips. We do not have enough training data for this case). TABLE III shows the performances of ITMR system on inter freeway ramps. A total of 11 different inter freeway ramps are evaluated using 107 recorded trips. The average performance of ITMR on inter freeway ramps is 3.7973 mph with 47.97% improvement over the baseline system that did not use a KB for speed profile prediction.

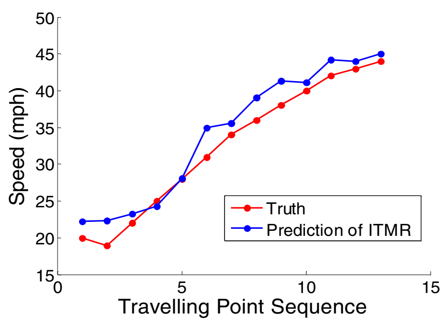


Fig.12. An example of speed profile prediction on the freeway entering ramp.

TABLE II. Freeway Enterin Ramp Experiment Result

Ramp Category	Testing Ramps	Used ramps for Training	Prediction MAE with KB (mph)	Prediction MAE without KB (mph)
#1	Ramp10	Ramp1	3.6903	4.3263
	Ramp1	Ramp10	4.2617	5.9695
#2	Ramp15	Ramp3, Ramp14	7.7241	10.6294
	Ramp14	Ramp3, Ramp15	4.4692	6.1737
	Ramp3	Ramp14, Ramp15	11.0047	7.8686
#3	Ramp13	Ramp5	2.3593	4.6438
	Ramp5	Ramp13	4.6383	6.0984
#4	Ramp16	Ramp7, Ramp9, Ramp12,	5.9741	7.9952
	Ramp12	Ramp7, Ramp9, Ramp16	4.7657	13.0265
	Ramp9	Ramp7, Ramp12, Ramp16	3.2708	6.7263
	Ramp7	Ramp9, Ramp12, Ramp16,	1.7600	10.1922
#5	Ramp11	Ramp8	20.6169	21.2314
	Ramp8	Ramp11	22.5464	22.4489

TABLE III. INTER RAMP EXPERIEMT RESULTS

Ramp Category	Testing Ramps	Used ramps for Training	Prediction MAE with KB (mph)	Prediction MAE without KB (mph)
#6	Ramp6	Ramp1	4.2886	12.4727
	Ramp1	Ramp6	5.4190	9.7837
#7	Ramp9	Ramp3	6.8006	14.6241
	Ramp3	Ramp9	2.5033	4.4217
#8	Ramp5	Ramp4	3.2151	5.3152
	Ramp4	Ramp5	3.4625	5.8590

The example of speed profile prediction on freeway exit ramps by the ITMR system is presented in Fig. 13. The speed profile is predicted on I-94E to Ann Arbor Saline Rd. in Ann Arbor, Michigan, U.S.A. The true recorded speed profile is superimposed with red color in the same figure. In this example, the MAE of the proposed ITMR system is 3.5079 mph. The overall performance of the proposed ITMR system on freeway exit ramps is presented in TABLE IV. A total of 13 different freeway exit ramps are evaluated using 276 real driving recorded trips. The average performance of ITMR on freeway exit ramp is 8.3619 mph which is a 4.54% improvement over the system that does not used KB for speed profile prediction.

V. CONCLUSION

We have presented an Intelligent Trip Modeling on Ramp (ITMR) system to predict speed profiles on freeway ramps. The ITMR system consists of a ramp classification decision tree, a knowledge base built with individual historical driving data, and speed profile prediction neural networks, RSPPNN. The ITMR system was fully implemented and evaluated using real driving data recorded by probe vehicles. The performance of the ITMR system shows that the proposed method can predict speed profiles on any ramps precisely and outperforms the baseline that does not use the knowledge base built with the historical individual driving data. Currently we are working on understanding the effect of different NN architectures and individual driving behavior by analyzing individual driving data to improve the performance further.

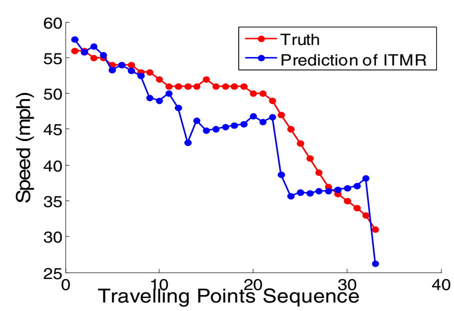


Fig. 13. An example of speed profile prediction on the freeway exit ramp.

TABLE IV. FREEWAY EXIT RAMP EXPERIEMT RESULTS

Ramp Category	Testing Ramps	Used ramps for Training	Prediction MAE with KB (mph)	Prediction MAE without KB (mph)
#9	Ramp6	Ramp1, Ramp3, Ramp4	4.8720	16.8127
	Ramp4	Ramp1, Ramp3, Ramp6	4.1534	7.8864
	Ramp3	Ramp1, Ramp4, Ramp6	4.9236	6.5274
	Ramp1	Ramp3, Ramp4, Ramp6	9.3055	10.3761
#10	Ramp10	Ramp2, Ramp5, Ramp7	10.3976	7.6881
	Ramp7	Ramp2, Ramp5, Ramp10	11.2909	12.9858
	Ramp5	Ramp2, Ramp7, Ramp10	10.9189	8.4123
	Ramp2	Ramp5, Ramp7, Ramp10	12.5309	9.4632
#11	Ramp11	Ramp9	4.8849	6.9413
	Ramp9	Ramp11	4.9796	18.4676

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