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Connected Vehicle-Based Lane Selection Assistance Application

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***Abstract*— Connected vehicle (CV) technology has great potential to improve the performance of today's advanced driver assistance systems in terms of safety, energy efficiency, and driving comfort. The aim of this paper is to develop a specific CV application that assists with lane selection, i.e., finding the best travel lane in terms of travel time based on predicted lane-level traffic states. In this paper, a spatial-temporal model (ST-model) was developed, which utilizes spatial and temporal information of road cells to predict future traffic states. This information was used by the proposed lane selection assistance application to select an optimal lane sequence for the application-equipped vehicle. A comprehensive simulation-based evaluation was then conducted under various scenarios, e.g., with different traffic volumes, penetration rates of communication-capable vehicles, and information update cycles. The evaluation results reveal several interesting findings, including: 1) the proposed ST-model outperforms the basic estimation model in terms of traffic state prediction accuracy; 2) travel times of application-equipped vehicles can be reduced by up to 8% with the use of the proposed lane selection assistance application when compared with the baseline, under various traffic scenarios; 3) the application can be effective in the early deployment stage of CV technology, where the penetration rate of communication-capable vehicles is still low; and 4) the potential conflict risk of application-equipped vehicles is reduced, although the application is mainly designed for mobility benefits, due to the more strategic and informed lane changes suggested by the proposed application.**

***Index Terms*— Connected vehicles, lane selection assistance, lane-level traffic state prediction, optimization, spatial-temporal discretization.**

I. Introduction

IN RECENT years, Connected Vehicle (CV) technology that enables wireless communications among vehicles as well as between vehicle and infrastructure (V2X) plays an important role in the evolution of advanced driver assistance systems (ADAS), for improving vehicle safety, efficiency, and driving comfort [1], [2]. Various studies have been conducted on the methods for V2X data exchange [3]–[5]. Current CV applications are designed mainly based on two types of communications: Wireless Access in the Vehicular Environment (WAVE) based Dedicated Short-Range Communications (DSRC) and cellular based communications. DSRC devices are capable of providing high availability and low latency channels for critical safety applications [6] through the IEEE 802.11p standard [7] especially designed for automobile communication, but they require relatively expensive on-board units for every communication-capable terminal [2]. On the other hand, cellular-based devices (e.g., smartphone) can be easily integrated with different ADAS due to the availability of various built-in sensors.

The CV technology has attracted increased attention due to its great potential to enhance vehicle and road safety [8]–[12], environmental sustainability [1] and driving comfort [13], [14]. For example, Schildbach and Borrelli focused on the safety of lane changes on highway and designed safe lane change trajectories for drivers using predictive control models [8]. Wu *et al.* [1] proposed an Eco-Approach and Departure (EAD) application which can receive signal phase and timing information from the upcoming traffic signal to better guide the driver through the intersection in an environmentally-friendly way. Similarly, Butakov and Ioannou [13] proposed an in-vehicle system which uses traffic light location and timing to find an individual optimal driving pace. Moreover, a number of effort has been made by different agencies to advance and promote CV research. For instance, the Connected Vehicle Reference Implementation Architecture [15] summarized a large number of applications developed under the Safety Pilot program [16], the Dynamic Mobility Application program [17], the Applications for the Environment: Real-time Information Synthesis program [18], and the Road Weather Connected Vehicle Applications program [19] funded by the U.S. Department of Transportation (USDOT). Also, the European Union and other countries funded several projects on the development of CV applications [20], [21].

Although a large number of CV applications have been proposed and developed for driving assistance, only a small number of them are focused on lateral control assistance. Examples include lane assignment [22], [23] and optimal lane selection [24]. Dao *et al.* [22], [23] presented a decentralized lane assignment approach for a group of single vehicles or vehicle platoons within the vicinity of on/off ramps (entries and exits) via inter-vehicle communication. Another research effort on lane selection was proposed to regulate freeway uncoordinated lane changes via two-way Vehicle-to-Infrastructure (V2I) communication, by minimizing potential

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vehicle conflicts [24]. The results in [24] showed that, due to the regulated lane-changing behaviors, the mean average travel time is reduced (by 0.57% to 3.79%) as compared to the non-lane selection scenario. These studies all hold a strong assumption that all the vehicles on the freeway are application-equipped vehicles (under control), which makes it challenging to implement these lane assignment approaches in practice within the next ten years or more. Even so, mobility-focused lateral control assistance ADAS still has not been very well studied yet so far.

On the other hand, traffic state prediction has been well studied for years using statistical models, such as Kalman filtering, nonparametric regression models, or neural networks [25]–[29]. Kwon *et al.* [25] predicted travel times on freeway using a linear regression model based on measurements from loop detectors . Rice and Zwet [26] proposed a simple robust time-series model for travel time prediction for a section of a freeway. At the same time, many model-driven and data-driven algorithms have been proposed for short-term traffic state prediction, such as Hidden Markov Models [30], [31], K-nearest neighbors approach for traffic state prediction [32], Particle Filter algorithm [33], [34], Kalman Filter [35], and deep neural networks [36].

A few Markov chain based traffic forecasting methods has been developed [31], [37]. The Markov chain (discrete) model was mainly used to decide the traffic state of the next interval based on the traffic model. For example, nearest neighbor classification in combination with variable-length Markov chains was used to predict the traffic pattern [31]. After the traffic state of each new time step is classified into a cluster, the specific speed value is estimated using the appropriate locally weighted regression model which is trained with data only from the relevant cluster. In addition, a combined forecasting method based on Markov chain theory and Grey Verhulst model was proposed for high prediction accuracy of short-term traffic flow forecasting method [37]. In order to improve the accuracy of forecasting, the volatility of data is dealt with by Markov chain theory on the basis of Grey Verhulst model. The results show that the relative error (between real-world data and prediction data) of traffic flow of one road segment across 16 time steps (5 min per time step) ranges from 0% to 13%.

At the same time, a short-term traffic prediction method based on spatial-temporal correlations was also proposed. In [38], Pan and Wynter brought up that the traffic state of a specific site is highly affected by its upstream and downstream traffic conditions; and free-flow speeds are spatially correlated (cell-to-cell, lane-to-lane correlated). An extended stochastic cell transmission model (SCTM) was used to support short-term traffic state prediction, taking into account the spatial-temporal correlation of traffic flow. In [38], a section of I210-W was divided into four cells, with about 0.5 mile per cell. The overall mean absolute percentage error (MAPE) was calculated for effectiveness validation, which was around 10.8%-14% [38]. In [39], a traffic state estimation approach was proposed, which utilizes road network correlation and sparse traffic sampling to estimate the traffic conditions of different road segments. This method derives Multiple Linear Regression (MLR) based mathematical model to represent traffic relations and applies both the MLR model and the compressive sensing technique to achieve a city-scale traffic estimation via tracking a small number of probe vehicles. The traffic estimation model was validated by extensive trace-driven experiments with real-world traffic data (within a large network with 1826 road segments in Shanghai city). Results show that the absolute speed differences between the estimated results and the pseudo ground truths over different traffic scenarios are 5.2 km/h to 11.0 km/h (around 3.23 mph to 6.84 mph).

Another approach to traffic state estimation and prediction is to use an improved Ensemble Kalman Filter to estimate and predict realistic large-scale freeway network, whose computation time can be decreased due to smaller matrix inversions [35]. In [36], a machine learning deep neural network was adopted to model the evolution of the traffic state in a freeway. However, all these approaches mentioned are focused on link level traffic state prediction instead of lane level. At the same time, studies of lane-based methods have attracted more and more attention recently, including but not limit to vehicle trajectory predictions, queue warning effectiveness analysis and lateral motion prediction of autonomous vehicles [40]–[42]. In order to support the implementation of lane-level applications in reality, there is also lane-level vehicle guidance technology, e.g., using enhanced GPS/multi-layer map model for ego-lane estimation and lane-level navigation service [43]–[46]. Also, advanced sensing devices have been developed as the key enabler for accurate position tracking, such as the Radio Frequency IDentification (RFID) technology [47], [48], which will support numerous applications in transportation in the future [49]. Inspired by the work mentioned above, we proposed a regression model for lane-level traffic state prediction by utilizing traffic state correlations between adjacent road segments along the same lane (intra-lane information) and across the adjacent lanes (inter-lane information).

In this study, we propose a lane selection assistance application to help the driver find an optimal lane-level "micro" route in terms of minimizing the travel time. The decision making process is based on the prediction of traffic states at the lane level via connected vehicle technology (e.g., cellular network). The rest of this paper is organized as follows: Section II presents the problem formulation, followed by the detailed description of the lane selection algorithm, system architecture and the proposed spatial-temporal traffic state prediction model in Section III. Simulation model and scenarios are introduced in Section IV. In Section V, simulation studies are conducted to evaluate the performance of the proposed application by varying different parameters, such as traffic congestion level, penetration rate of communication-capable vehicles, and information update cycle. The last section concludes this paper with further discussion on future work.

II. Problem Formulation

In the real world, drivers usually perform lane changes based on their observations within sight distance, many of which are not well planned. For example, consider a target

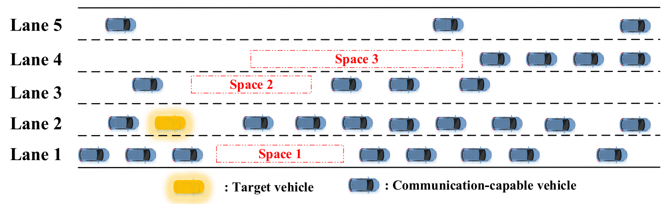


Fig. 1. An example of the problem description.

vehicle (the individual vehicle of interest) driving on a 5-lane freeway under heavy traffic conditions (see Fig. 1). Since the traffic downstream of the target vehicle (in lane 2) is congested within the range of the driver's vision, the target vehicle driver needs to make a decision on which lane to change to (i.e., space 1 in lane 1 or space 2 in lane 3). Because of the limited sight distance, it is hard for the driver to know exactly which lane has lighter traffic. Assume that the driver changes to space 2 in lane 3 and he/she will face two alternatives again, changing to space 3 in lane 4 or staying in lane 3. The driver would probably change to space 3 in lane 4 rather than staying in lane 3 since there is more room in space 3. However, a congestion shockwave could be propagating from the downstream to the upstream in lane 4 (beyond the range of the driver's vision) at the same time. In this circumstance, staying in space 2 in lane 3 might be a better choice. Therefore, in order to obtain mobility benefits, predicted information of downstream traffic at the lane-level is essential for drivers to make smarter choices on lane selection.

We define vehicles which could share their basic information (e.g., velocity and position) as communication-capable vehicles, and define vehicles equipped with the proposed application as application-equipped vehicles. In this study, we assume cellular-based connectivity for data collection is available (see Fig. 2). We assume that sending messages over the cellular network in an end-to-end manner is technically feasible. An application-equipped vehicle is always communication-capable, but a communication-capable vehicle is not necessarily application-equipped. Communication-capable vehicles can send their activity information to a centralized center via on-board smartphones with built-in sensors for traffic/vehicle states prediction. Based on the data collected from on-road communication-capable vehicles, the traffic state (e.g., average speed) can be estimated and even predicted with certain models by an application server (or the traffic management center, or the cloud center). The application server stores and broadcasts the prediction results to the application-equipped vehicles so that the proposed application can support the decision-making process of lane changing. We also assume that vehicles have complete knowledge of which lane it is in (this is a research problem in itself).

Note that the traffic state changes with time, therefore dynamic models are needed to forecast the traffic state. The lane-level traffic state prediction can be conducted using regression models. Aimed at searching for the best lane-level path for an application-equipped vehicle, an optimization problem is formulated to determine which space (e.g., a lane-level segment) the vehicle should occupy at certain time.

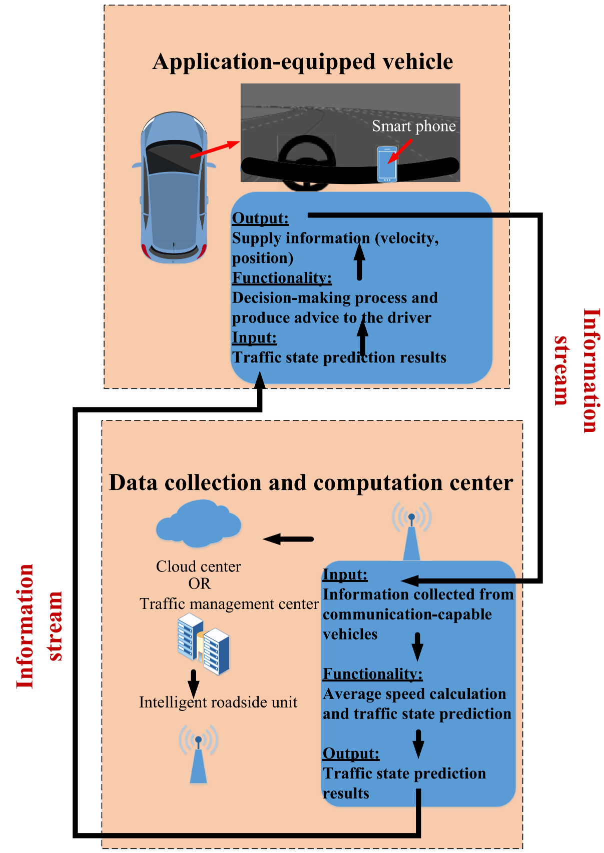


Fig. 2. Information flow of the lane selection assistance application.

III. Proposed Lane Selection Assistance Application

To solve this problem, a detailed three-step approach is proposed: 1) spatial-temporal discretization of roadway network; 2) data-driven traffic state prediction at the lane level; 3) optimal lane sequence identification based on dynamic programming (DP).

A. Spatial-Temporal Discretization

As shown in Fig. 3, the road network can be divided into K road segments and $K \times I$ cells, where I is the total number of lanes of interest. To make this approach more feasible and reduce the complexity for implementation, we did not include those "discontinuous lanes of the mainline" as the lanes of our interest in this study. These discontinuous lanes of the mainline include where mandatory lane changes have to be performed, such as auxiliary lane(s) before lane-drop areas (e.g., lane m and lane n in Fig. 3). Another major assumption is that there exists speed difference across different lanes especially in heavy traffic. Usually fluctuations of traffic may be caused by the mainline vehicles which make mandatory lane changes to leave the freeway from the off-ramp exit, or the influx of traffic from the on-ramp. These factors cause large speed difference among lanes, especially in heavy traffic.

The spatial discretization method is more applicable to freeways where road segments of same traffic direction are correlated with each other. It might be more challenging for

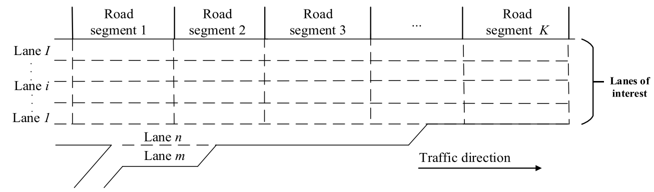


Fig. 3. Sketch map of spatial discretization on freeways.

urban areas and intersections. Some details about the spatial segment discretization are as follows:

- The length of each segment does not have to be the same.
- A segment should have consistent geometric characteristics throughout.
- Optimal segment length, varying with traffic speed, balances between capturing the variability in traffic state versus limiting the size of optimization problem.

The road stretch used in this paper is California SR91-E, a 15-mile corridor with 4 to 6 lanes and ten pairs of on/off-ramps (see Section IV.A for more details). The spatial discretization in this paper was done offline, splitting this freeway into 15 road segments, almost each of which is about one mile long. The approach can be extended to different freeways as a generalized method, however it could be slightly different for various road ways, depending on the traffic direction and specific road geography.

B. Lane-Level Traffic State Prediction

For each cell in Fig. 3, we can further define the associated traffic state that can be used to guide the lane change. We do not estimate the traffic state of the discontinuous lanes ("non-of-interest" lane) of the mainline, such as auxiliary lane(s) before lane-drop areas (e.g., lane m and lane n in Fig. 3). In this study, we assume that the communication-capable vehicles can transmit their state information such as instantaneous speed and location (both longitudinal and lateral with lane-level accuracy) over the entire roadway network in real-time. Then the lane-level average speed of each road segment at each time step can be estimated and used as the critical traffic state. More specifically,

$$x_{i,k}(n) = \frac{VMT_{i,k}(n)}{VHT_{i,k}(n)} \quad \forall i \in I,\ k \in K \tag{1}$$

where $x_{i,k}(n)$ is the average speed on lane i of road segment k within the n-th time interval, $n \cdot \Delta T$. VMT and VHT represent the vehicle miles traveled and vehicle hours traveled, respectively. Assuming the time interval ΔT at each step is uniform, the average speed can be also estimated by the ratio of the sum of all sampled speeds to the total number of speed samples for all vehicles of interest. In addition, we use a fixed average speed value (65 mph in this study) to represent the traffic state $x_{i,k}(n)$, when no communication-capable vehicle is available in the specific cell.

It has been brought up that the traffic state of a specific site is highly affected by its upstream and downstream traffic conditions, and free-flow speeds are spatially correlated (cell-to-cell, lane-to-lane correlated) [38]. Inspired by the aforementioned research, we propose a linear regression model (referred to as Spatial-Temporal model or ST-model in this paper) for traffic state (i.e., average speed) prediction at the lane level by utilizing traffic state association between adjacent road segments along the same lane (intra-lane information) and across the adjacent lanes of both sides (inter-lane information) during consecutive time steps, in order to serve as the basis of the lane selection algorithm proposed in Section III.C.

Considering the lane-based impacts on traffic state prediction, we herein utilize both intra-lane and inter-lane traffic state information for traffic state prediction. Therefore, the linear regression model of one single lane is defined as

$$\vec{X}_i(n) = A_i \vec{X}_{mi}(n-1) + \vec{u}_i \quad \forall i \in I \tag{2}$$

which can be extended as Equation (3), as shown at the top of the next page. In Equation (3), the output variable matrix is $\vec{X}_i(n) \in R^{K\times 1}$; input variables matrix is multiple lanes' traffic state $\vec{X}_{mi}(n-1) \in R^{3K\times 1}$; coefficient matrix is $A_i \in R^{K\times 3K}$ (considering the impacts from immediate downstream and upstream segments of the original lane and adjacent lanes); and intercept matrix is $\vec{u}_i \in R^{K\times 1}$. The coefficient and intercept matrices of the above linear regression model can be trained by historical data. In this study, we assume that the i-th lane traffic state on road segment k during the n-th time interval, $x_{i,k}(n)$, can be represented by a linear function of the lane-level traffic states on road segments $k-1$ (immediate upstream), k and $k+1$ (immediate downstream) of the original lane and adjacent lanes of both sides, during the $(n-1)$-th time interval, i.e., $x_{i-1,k-1}(n-1)$, $x_{i-1,k}(n-1)$, $x_{i-1,k+1}(n-1)$, $x_{i,k-1}(n-1)$, $x_{i,k}(n-1)$, $x_{i,k+1}(n-1)$, $x_{i+1,k-1}(n-1)$, $x_{i+1,k}(n-1)$ and $x_{i+1,k+1}(n-1)$. Please note that the Equation (3) is the general form, only one-side adjacent lane was considered for the left-most lane (or the right-most lane).

The full linear regression model of the entire network with K segments and I lanes of interest can be formulated as follows:

$$\begin{bmatrix} \vec{X}_1(n) \\ \vec{X}_2(n) \\ \vdots \\ \vec{X}_I(n) \end{bmatrix} = \begin{bmatrix} A_1 & & & \\ & A_2 & & \\ & & \ddots & \\ & & & A_I \end{bmatrix} \begin{bmatrix} \vec{X}_{m1}(n-1) \\ \vec{X}_{m2}(n-1) \\ \vdots \\ \vec{X}_{mI}(n-1) \end{bmatrix} + \begin{bmatrix} \vec{u}_1 \\ \vec{u}_2 \\ \vdots \\ \vec{u}_I \end{bmatrix} \tag{4}$$

For comparison purpose, we also evaluated another simple traffic state prediction model (as a baseline), which used the traffic state in the last time step as the predicted state in the current time step without considering the spatial interaction (similar estimation model was also proposed in [50]), i.e.,

$$x_{i,k}(n) = x_{i,k}(n-1) \tag{5}$$

Therefore, for lane i, the baseline can be simply written as

$$\vec{X}_i(n) = \vec{X}_i(n-1) \tag{6}$$

$$
\begin{bmatrix} x_{i,1}(n) \\ x_{i,2}(n) \\ x_{i,3}(n) \\ \vdots \\ x_{i,k}(n) \\ \vdots \\ x_{i,K}(n) \end{bmatrix}
= \begin{bmatrix}
a_{i-1,1} & a_{i-1,2} & \cdots & a_{i,1} & a_{i,2} & \cdots & a_{i+1,1} & a_{i+1,2} & \cdots \\
a_{i-1,1} & a_{i-1,2} & a_{i-1,3} & \cdots & a_{i,1} & a_{i,2} & a_{i,3} & \cdots & a_{i+1,1} & a_{i+1,2} & a_{i+1,3} & \cdots \\
& a_{i-1,2} & a_{i-1,3} & a_{i-1,4} & \cdots & a_{i,2} & a_{i,3} & a_{i,4} & \cdots & a_{i+1,2} & a_{i+1,3} & a_{i+1,4} & \cdots \\
& & & & & \ddots \\
& & a_{i-1,k-1} & a_{i-1,k} & a_{i-1,k+1} & \cdots & a_{i,k-1} & a_{i,k} & a_{i,k+1} & \cdots & a_{i+1,k-1} & a_{i+1,k} & a_{i+1,k+1} & \cdots \\
& & & & & & \ddots \\
& & & & & a_{i-1,K-1} & a_{i-1,K} & \cdots & a_{i,K-1} & a_{i,K} & \cdots & a_{i+1,K-1} & a_{i+1,K}
\end{bmatrix}
$$

$$
\times \begin{bmatrix} x_{i-1,1}(n-1) \\ \vdots \\ x_{i-1,k}(n-1) \\ \vdots \\ x_{i-1,K}(n-1) \\ x_{i,1}(n-1) \\ \vdots \\ x_{i,k}(n-1) \\ \vdots \\ x_{i,K}(n-1) \\ x_{i+1,1}(n-1) \\ \vdots \\ x_{i+1,k}(n-1) \\ \vdots \\ x_{i+1,K}(n-1) \end{bmatrix} + \vec{u}_i \tag{3}
$$

and for the entire network,

$$
\begin{bmatrix} \vec{X}_1(n) \\ \vec{X}_2(n) \\ \vdots \\ \vec{X}_I(n) \end{bmatrix} = \begin{bmatrix} \vec{X}_1(n-1) \\ \vec{X}_2(n-1) \\ \vdots \\ \vec{X}_I(n-1) \end{bmatrix} \tag{7}
$$

More details on the comparison results between the ST-model and the basic estimation model in terms of traffic state prediction will be presented in Section V.B.2).b).

C. Optimal Lane Selection Algorithm

As previously mentioned, the objective of the proposed lane selection assistance application is to improve the mobility performance of application-equipped vehicles. With the spatial-temporal discretization of the entire roadway network, we formulate the problem as dynamically searching a lane-level path that maximizes the sum of average speed of each lane segment that the vehicle traverses. The variables of optimal solutions are the binary variables $\omega_{i,k}(n)$ given the system equations of lane-level traffic states $x_{i,k}(n)$. The optimization problem is solved only for the next N-min (an information update cycle). Assume that the ego application-equipped vehicle is on lane p of segment q. To obtain the optimal lane index solution for time step n, the objective function and constraints of the ego application-equipped vehicle are shown as follows:

$$
\max_{\Omega(n)} \sum\nolimits_{i=1}^{I} \sum\nolimits_{k=q}^{K} \omega_{i,k}(n)\, x_{i,k}(n) \tag{8}
$$

$$
\textbf{\textit{s.t.}} \quad \begin{bmatrix} \vec{X}_1(n) \\ \vec{X}_2(n) \\ \vdots \\ \vec{X}_I(n) \end{bmatrix} = \begin{bmatrix} A_1 & & & \\ & A_2 & & \\ & & \ddots & \\ & & & A_I \end{bmatrix} \times \begin{bmatrix} \vec{X}_{m1}(n-1) \\ \vec{X}_{m2}(n-1) \\ \vdots \\ \vec{X}_{mI}(n-1) \end{bmatrix} + \begin{bmatrix} \vec{u}_1 \\ \vec{u}_2 \\ \vdots \\ \vec{u}_I \end{bmatrix} \tag{9}
$$

$$
\omega_{i,k}(n) \in \{0, 1\} \quad \forall i \in [1, I], \quad \forall k \in [1, K] \tag{10}
$$

$$
\sum\nolimits_{i=1}^{I} \omega_{i,k}(n) = 1, \quad k \in [q, K] \tag{11}
$$

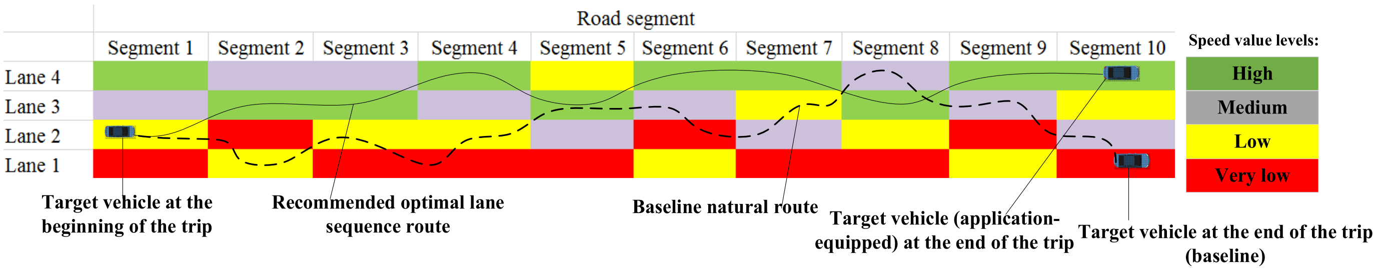


Fig. 4. An illustrative example of the optimal lane-level path in a discretized roadway network.

$$\text{If } \omega_{i,k}(n) = 1, \text{ then } \omega_{j,k+1}(n) = 1,$$

$$\forall i \in [1, I], \quad j = i-1, or\ i, or\ i+1,\ k \in [q, K-1] \quad (12)$$

where I is number of lanes of interest, K is number of road segments, and n is the next N-min time step (length of the prediction window). The aforementioned lane-level traffic state prediction model is used as a constraint to drive the evolution of traffic states (see (9)). As mentioned above, $\omega_{i,k}(n)$ is a 0-1 binary variable indicating if the target vehicle is present ($\omega_{i,k}(n) = 1$) or not ($\omega_{i,k}(n) = 0$) on lane i of road segment k during time interval n (see (10)). Equation (11) guarantees that at any time step, the target vehicle would be only present in one cell for each road segment k. The last if-then constraint (i.e., (12)) denotes that the solution $\Omega(n)$ only allows adjacent lane changes within one N-min time step. The solution $\Omega(n)$ (i.e., optimal lane-level micro-routing from the current road segment q to road segment K, within the next N-min) is obtained by Dynamic Programming (DP) [51], based on traffic status of time step $n-1$.

The proposed lane selection assistance application is implemented through the application programming interface (API) in PARAMICS microscopic traffic simulation tool [52]. Fig. 4 presents an illustrative example of optimal lane-level path (as time elapses) calculated by the proposed lane selection assistance algorithm (with spatial discretization of roadway network). The average speeds of each road segment in different lanes are grouped into different levels: very low, low, medium and high, which are represented by different colors in Fig. 4. Since the lane-level speed is time-varying, we don't assign fixed speed partition range for each level. The purpose of defining different levels in Fig. 4 is to show the spatial discretization and the lane-level traffic state more intuitively. Note that the speed levels of lanes in each road segment are updated every N-min information collection cycle. Compared to the unguided path (baseline), the target vehicle (application-equipped) follows the optimal lane sequence during the whole trip based on the time-varying lane-level traffic state prediction results, aiming to minimize the travel time over the same length of distance traveled. It is possible but not necessary that the application-equipped vehicles change lanes only at cell boundaries (Fig.4 is a schematic diagram). After changing to the target lane, the target vehicle is restricted to the corresponding target lane without performing any extra lane changes. The proposed lane selection assistance algorithm is shown in Table I.

TABLE I
LANE SELECTION ASSISTANCE ALGORITHM

Algorithm Lane Selection Assistance Algorithm

Input: 1. Traffic state at (n-1)-th N-min
Output:2. **Identify** the Level of Service of current traffic state
3. **Apply** corresponding regression model
4. **Predict** the n-th N-min traffic state
5. **Update** the optimal lane sequence
6. **Follow** current optimal lane-level route
7. **Accumulate** travel time t
8. **if** in the middle of trip **do**
  if t > update period **do**
    Update N-min step index $n = n+1$
    Do *step* 1
  else Do *step* 6
  end if
end if

In summary, with discretization of roadway network (in time and lane-level space), the proposed lane selection assistance application can be implemented as depicted in Table I:

1) *Model training for lane-level traffic state prediction*. The linear regression model (i.e., matrix A and vector $\vec{u}$) for state prediction can be trained (even offline) by real-world traffic data and can be differentiated by various traffic conditions or Level of Service (LOS) defined in Highway Capacity Manual [53]. In the following simulation study, we trained different models for LOS C (free flow), LOS D (transitional flows) and LOS E (unstable flows), respectively, to cover three representative levels of congestion.
2) *Online guidance of optimal lane for the next time steps*. With the most updated prediction of lane-level traffic state downstream, the optimization problem is solved to determine the best lane for the target vehicle (following the steps described in (8) through (12)). A table of the lane index sequence for every road segment is generated/updated online for the application-equipped vehicles. For online implementation, a rolling horizon technique [54] is applied where the optimization problem is solved within every N-min information update cycle, based on the updated prediction of downstream traffic states (at the lane level).

IV. SIMULATION SETUP

To validate the proposed application, we conduct a comprehensive simulation study as described below.

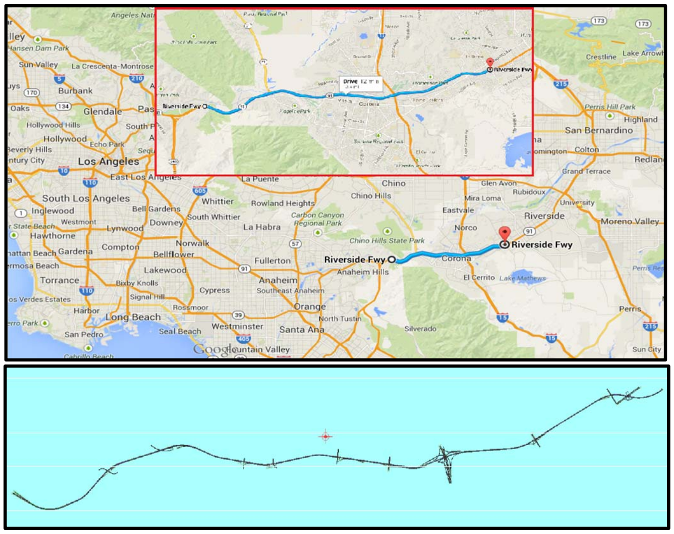


Fig. 5. Road network of the California SR-91E in real-world and PARAMICS.

A. Simulation Network Model

The simulation network is California's SR-91(eastbound), consisting of a 15-mile corridor located between the Orange County Line and Tyler Street in Riverside (see Fig. 5). The number of lanes varies from 4 to 6, and there are ten on/off-ramp pairs. The traffic demand (25,000 vehicles released in the network, stable traffic flow) and driving behavior have been well calibrated against a typical weekday morning in the summer of Year 2006 based on historical traffic data from California Freeway Performance System (PeMS) to represent the network's real-world conditions [55]. In this study, we use PARAMICS (PARAllel MICroscopic Simulator), a microscopic traffic simulation tool that is capable of modeling the movement and behavior of each individual vehicle on road networks, to generate detailed traffic data (i.e., to simulate as in a connected environment) for system performance evaluation.

B. Implementation Details

Traffic state prediction model's inputs were generated from the simulation network. Those raw data were post processed by aggregating and averaging for different road segments and lanes at different time horizons which were afterwards trained using the regression model ("fitlm" function) with ordinary least squares in MATLAB.

The optimization process is implemented online through the application programming interface (API) in PARAMICS microscopic traffic simulation tool using C++ language. In the PARAMICS API, the obtained prediction model coefficients are applied to real-time collected data to acquire traffic state prediction results. After the prediction was made, recursion method of dynamic programming algorithm is used to obtain the optimal solution (i.e., the lane index sequence for the current road segment the vehicle was traveling on and every road segment downstream). Within the N-min duration, the target lane index is assigned to the application-equipped vehicle based on its optimal lane index sequence.

C. Simulation Scenarios

To test the lane selection assistance application, we divided the road stretch into about fifteen 1-mile road segments and chose a specified traffic information update cycle. The simulation period is from 6:00 AM to 9:00 AM with a 15-minute warm-up period. From 6:16 AM to 7:51 AM (to guarantee the last target vehicle can complete its trip by the end of simulation) with 5- minute intervals (called a case), there are 20 cases corresponding to 20 departure time intervals for each simulation run. At the start of each case (the first ten seconds), a few application-equipped vehicles (usually 4-6, i.e., a case) with the same Origin-Destination (OD) are randomly selected into the network for further effectiveness evaluation purpose. All the selected vehicles are released from the left end of the mainline and traveled to the right end of the mainline. In addition, since the number of lanes along the mainline ranges from 4 to 6, the lanes of interest herein only consist of the four left-most lanes (as conceptually illustrated in Fig. 3). The traffic direction is from left to right.

As mentioned above, 4-6 application-equipped vehicles in each case are released into the network at certain frequency (i.e., every 5 minutes) to evaluate the effectiveness of the proposed lane selection assistance application. Moreover, comprehensive sensitivity tests are conducted over the following system parameters:

- *Congestion level*. With a major focus on the traffic pattern, three networked traffic volumes that represent free flow, medium and heavy traffic are evaluated: 16,000 vehicles/simulation run, 25,000 vehicles/simulation run and 32,000 vehicles/simulation run. An analysis on average traffic speed indicates that these three levels of traffic demand correspond to LOS C (free flow), LOS D (transition flows) and LOS E (unstable flows), respectively, according to the Highway Capacity Manual (HCM) 2010 53]. For LOS C, LOS D (calibrated) and LOS E cases, results of 100% penetration rate of communication-capable vehicles are investigated for the sensitivity analysis on congestion level.
- *Penetration rate of communication-capable vehicles*. Ten levels of penetration rate of communication-capable vehicles are studied in this paper, including 0.01%, 1%, 2%, 5%, 10%, 20%, 40%, 60%, 80% and 100% in the penetration rate sensitivity analysis.
- *Information update cycle*. As aforementioned, N-min is a specific traffic information update cycle for the target vehicles, during which time real-time information is collected. The traffic predict results are updated every N-min and the optimal lane sequence is overwritten at the same time. A set of {1 min, 2 min, 3 min, 4 min, 5 min} is selected for the information update cycle sensitivity test in order to observe its impacts on travel time improvement. The information update cycle is also related to the penetration rate of communication-capable vehicles. The information update cycle may be shorter due to more sufficiently available data.

Under these simulation scenarios, a baseline case for each scenario is defined as the case where the vehicles make lane changes as normal without any assistance. We use PARAMICS default lane change model. The vehicles of the baseline would consider to change to another lane when it needs to overtake a slow vehicle in front, taking into consideration its accepted gap at the same time. For more detailed information, please refer to [56]. On the other hand, the application-equipped vehicles would follow the lane selection guidance and make lane changes to the target lane smoothly in the simulation environment. As soon as the target lane was assigned, the optimal lane selection application-equipped vehicles would follow the recommendation of the target lane number and make lane changes as quickly as it can to get into its lane range but in a safe manner.

We conduct simulations with ten random seed numbers, generating 800-1200 (i.e., 10 seeds*20 departure time*(4-6 vehicles/departure time)) vehicle samples for each scenario and the corresponding baseline respectively. For every scenario, we compare the application-equipped vehicles with the same amount of non-application-equipped vehicles under the same environment (i.e., similar departure time, same OD and same traffic status). Moreover, for the same seed, the traffic status for both application-equipped vehicles and the corresponding baseline vehicles at the same departure time should be the same. "Travel time baseline" is calculated by averaging those baseline vehicles with the same departure time across ten seeds, and the average travel time of the application-equipped vehicles of ten seed of each departure time was compared with the corresponding "Travel time baseline". The performance of ST-model based traffic state prediction is evaluated in the simulation as well.

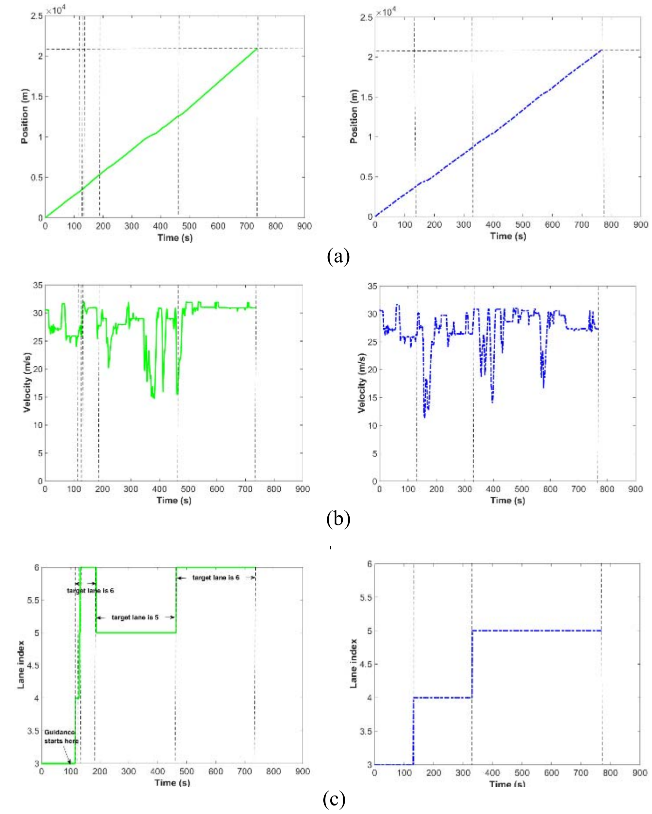


Fig. 6. An example of the application-equipped vehicle (left) and the corresponding baseline (right). (a) Trajectory. (b) Velocity. (c) Lane index.

V. Simulation Analysis

A. An Example of the Individual Vehicle

To give a general idea of how the proposed algorithm works, an example of the driving is analyzed in detail. Fig. 6 displays the driving features of one application-equipped vehicle (green solid line on the left) and the corresponding baseline vehicle (blue dashed lines on the right), respectively. Both vehicles start from the same lane with similar speeds and departure time (the departure time difference is within 10 seconds), and are assumed to get encountered the same traffic state. The time at each black vertical dashed line (except those at the end of the trip) is the time when a lane-changing maneuver happens. The individual vehicles are traveling under the relatively heavy traffic scenario (32000 vehicles/simulation run).

In the example of Fig. 6, the example vehicles are released at departure time 1 in the heavy traffic scenario. Fig. 6(a) shows that for the same distance, the vehicle equipped with the proposed application spends less travel time than the baseline vehicle whose driver changes lane without lane selection guidance. In Fig. 6(b), we can observe that the overall velocity of the application-equipped vehicle is higher than that of the baseline vehicle. After the guidance starts, the application-equipped vehicle is assigned to target lane 6 (see Fig. 6(c)). Please note that the target vehicle might cross several lanes at its current road segment to change to the target lane after the prediction results are updated.

In combination with Fig. 6(c), the lane changes of the baseline vehicle are more event-based operations, i.e., changing to an adjacent left lane to pursue a faster speed. On the other hand, we observe that, by taking full advantage of the long-range information, the proposed application would help the driver ahead of time make a better decision (in terms of lane index sequence) to obtain mobility benefits. Please note that non-adjacent lane changes might still happen at the beginning of the vehicle's trip or when the solution updates at each N-min, such as the lane changing behavior from lane 3 to the target lane 6 at the beginning of the vehicle's trip in Fig. 6(c).

B. Statistical Analysis of the Application Performance

In order to comprehensively test the robustness of the proposed lane selection assistance application, simulation results were obtained statistically as well.

1) Measures of Effectiveness (MOEs): To assess the mobility benefits of the lane selection assistance application, two types of performance measures were selected for statistical analysis as follows:

a) Forecast accuracy: Mean Absolute Percentage Error (MAPE) was used to measure the forecast errors from each trip of target vehicle:

$$MAPE = \frac{1}{n}\sum\nolimits_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100\% \tag{13}$$

where A_t is the actual value, F_t is the prediction value, and n is the total number of all samples involved in the

MAPE calculation. This MOE is used to evaluate the traffic average speed prediction accuracy for all the cases. In addition, due to the fact that these MOEs are less influenced by low average speed, we also use Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to evaluate the ST-model forecast accuracy under specific scenarios (e.g., the heavy traffic scenarios).

$$MAE = \frac{1}{n}\sum\nolimits_{t=1}^{n} |A_t - F_t| \tag{14}$$

$$RMSE = \sqrt{\frac{1}{n}\sum\nolimits_{t=1}^{n} (A_t - F_t)^2} \tag{15}$$

b) Performance of application-equipped vehicles: Relative Travel Time Difference (RTTD) is used to evaluate travel time difference between ST-model based scheme and baseline, i.e.,

$$RTTD_i = \frac{t_{ST}^i - t_B^i}{t_B^i} \times 100\% \tag{16}$$

where $RTTD_i$ is the relative travel time difference between ST-model based scheme and baseline at i-th departure time. t_{ST}^i is the mean travel time of 40-60 target vehicles at i-th departure time (as mentioned in Section IV.C), and t_B^i is the mean travel time of the corresponding baseline case at i-th departure time (same amount of vehicles with the application-equipped vehicles). This MOE shows mobility benefits in terms of individual travel time for the application-equipped vehicles portion (target vehicles) over the baseline (no-application). Again, to show the statistical significance, we ran simulation runs with ten random seeds, generating 800-1200 (i.e., 10 seeds*20 departure time* (4-6 vehicles/departure time)) vehicle samples for each scenario and the corresponding baseline, respectively.

In addition to RTTD, normalized conflict frequency is calculated for each individual vehicle based on the conflict occurrence results obtained from the Surrogate Safety Assessment Model (SSAM) [57], which is defined as potential conflict when the minimum time to collision drops below a predefined threshold (i.e., 3 seconds).

$$CF = \frac{\sum_{i=1}^{n} cn_i}{n} \tag{17}$$

where cn_i is the number of conflicts caused by vehicle i; n is the total number of vehicles. It is noted that in this study each conflict is only associated with the second vehicle (i.e., the one occupying the conflict area at a later instant) which is assumed to be responsible for the potential conflict.

2) Sensitivity Analysis: As aforementioned, sensitivity analysis is conducted on three parameters: congestion level, penetration rate of on-road communication-capable vehicles and N-min information update cycle. We use ten random number seeds for simulation. The test results are shown in boxplots, each of which contains 20 cases (i.e., 20 departure times) and there were 4-6 vehicles released for each case, thus one seed generating 80-120 vehicle samples for this scenario (ten seeds generating 800-1200 vehicle samples in total). The sample value of each departure time is the mean value calculated from 40-60 sample vehicles of the same case

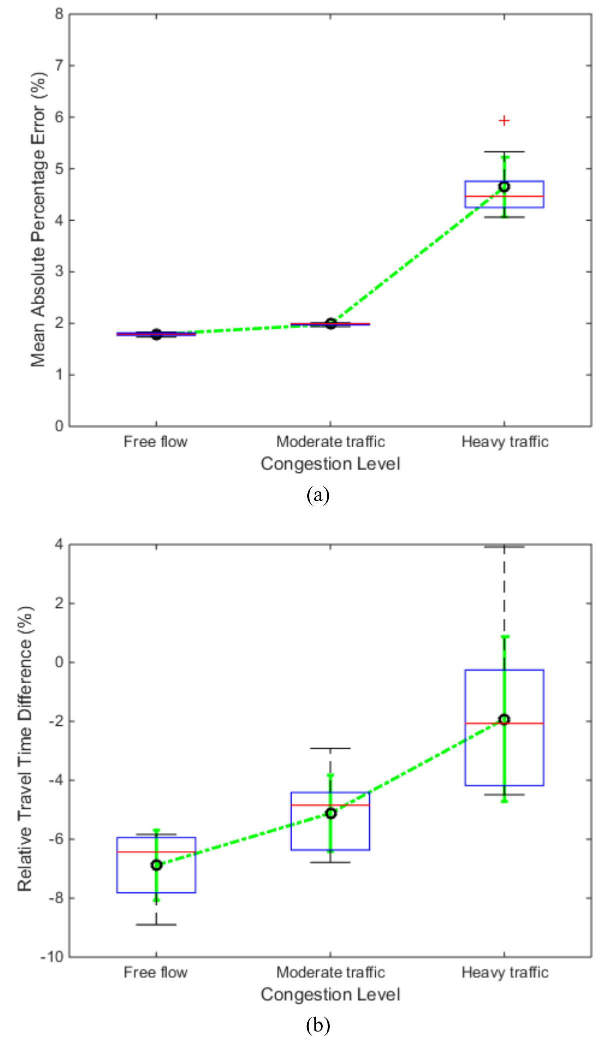


Fig. 7. Measures of effectiveness for different congestion levels. (a) Mean absolute percentage error. (b) Relative travel time difference.

with similar departure time and the same origin/destination, so is the baseline case. Therefore, for one scenario, the results were collected and compared between 800-1200 application-equipped vehicles, and 800-1200 vehicles of the corresponding baseline.

a) Sensitivity analysis on congestion level: Fig. 7 illustrates the results for three different traffic demands when the penetration rate of communication-capable vehicles was 100% at 1-min information update cycle. Every 1-min prediction cycle for each application-equipped vehicle has one MAPE value. Each MAPE value is calculated based on a comparison between the forecast and actual traffic state value of each cell across the four lanes of interest and 15 road segments. The final MAPE value for one application-equipped vehicle is calculated out by averaging all the MAPE values from multiple prediction cycles during its whole trip. We then average the MAPE values of application-equipped vehicles of each departure time, and draw the MAPE boxplot using 20 departure times' MAPE samples (each sample is the mean value of 40-60 target vehicles). It's worthy to mention that only from departure 1 to departure 10 cases are shown

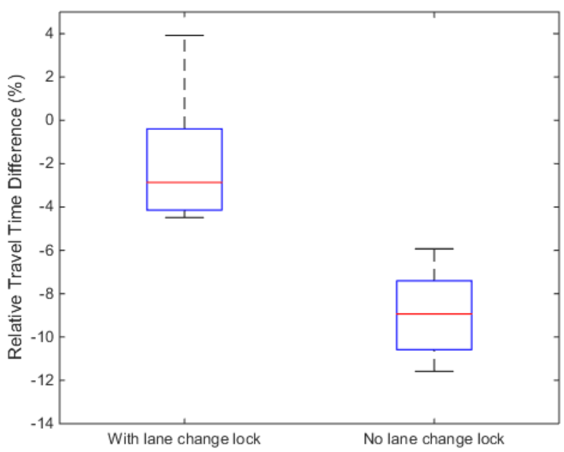


Fig. 8. Relative travel time difference with and without the lane change lock.

TABLE II

THE RECOMMENDED NUMBER AND THE ACTUAL LANE CHANGING NUMBER OF APPLICATION-EQUIPPED VEHICLES (1200 APPLICATION-EQUIPPED VEHICLE SAMPLES, 1-MIN INFO UPDATE CYCLE, 100% PENETRATION RATE OF COMMUNICATION-CAPABLE VEHICLES, 32,000 VEHICLES PER RUN)

Mean Value	***Baseline***	***1-min info cycle***
Recommendation number		34.55
Actual lane change	3.60	5.53

in Fig. 7 and Fig. 8. Since there exists too much bump-to-bump status (traffic breakdowns) after departure 10 in the heavy traffic scenario, the proposed prediction method generates large MAPE, so in Fig. 7 and Fig. 8 we do not include those vehicles which are beyond departure 10.

Fig. 7(a) displays the average speed prediction accuracy in terms of MAPE for three congestion levels (across 20 different departure time cases), which ranges from 1%-2% (for LOS C and LOS D). Assume the highest speed is 70 mph in the 25,000 veh/run case, the prediction error is less than 2 mph on average when traffic is stable and moderate, which could provide good prediction for the lane selection assistance application.

From Fig. 7(b), we observe the travel time improvement of the target vehicles is 5%-7% (median) compared with baseline under free flow and moderate traffic condition, whereas the travel time improvement is less (the median is around 2%) in the heavy traffic scenario.

In order to mimic the real-world lane change behavior, a three-second lock between two consecutive lane-changing operations for the application-equipped vehicles was set up to prevent too frequent/abrupt lane change. Moreover, we observe that the actual lane change number is less than the lane change recommendation number (see Table II) due to the limited time and space for performing lane changes, which could be the major reason for the less mobility improvement under the heavy traffic scenario.

TABLE III

THE AVERAGE VALUES FOR MAPE, MAE, AND RMSE IN THE HEAVY TRAFFIC SCENARIOS (100% PENETRATION RATE OF COMMUNICATION-CAPABLE VEHICLES, 32000 VEHICLES/RUN)

Mean Value	***Departures 1-10***	***Departures 11-20***
MAPE	4.64%	20.60%
MAE	2.49	4.36
RMSE	3.57	6.67

We also tested the relative travel time difference of the proposed application without the three-second lane change lock (see Fig.8), and results show that the relative travel time difference is significantly reduced in the heavy traffic scenario. The proposed lane selection assistance application is able to take advantages of the traffic state prediction scheme and be capable of dynamically guiding the driver for lane selection and thus can help squeeze the individual travel time, even under such unstable flows condition.

In addition, the forecast accuracy (MAPE, MAE and RMSE) of departures 11-20 in the heavy traffic status was evaluated as well (see Table III), in order to provide a more comprehensive assessment of the ST-model. Since the ST-model becomes less effective when there are too many traffic breakdowns, the prediction accuracy is lower, very likely leading to no benefits in the travel time improvement any more.

b) Sensitivity analysis on penetration rate of communication-capable vehicles: It is worthy to mention that, when the penetration rate is low, there may be not sufficient communication-capable vehicles inside a cell. As aforementioned in Section III.B, we set up a fixed average speed value for the cell with no communication-capable vehicles. In this study, the value used in simulation is 65 mph, which is the speed limit on most California highways. In the algorithm, once there exists one cell with no communication-capable vehicles, no target lane would be assigned to the target vehicles for that road segment. Moreover, we aim to show effects of a specific application at the stage of early deployment of connected vehicles based applications, and only a minority of vehicles were application-equipped in this paper. Specifically, there are about 4-6 application-equipped vehicles for each case (each departure time) for one run, appearing within the vicinity of each other, where we thus assume these application-equipped vehicles do not significantly affect each other.

In order to test the application reliability under various penetration rates, the application performance under different penetration rate levels of communication-capable vehicles was tested in the 25,000 veh/run case.

Fig. 9(a) summarizes the MAPE statistics results for ten levels of penetration rates (each containing 20 different departure time cases). The MAPE (median) concentrates on below 3% (starting from 20% penetration rate), which means that the performance of the ST-model is robust to the variation of high penetration rate of communication-capable vehicles which shows the application reliability to certain extent.

TABLE IV
THE AVERAGE VALUES OF MAPE, MAE, AND RMSE OF THE ST-MODEL AND THE BASIC ESTIMATION MODEL UNDER MODERATE TRAFFIC (100% PENETRATION RATE OF COMMUNICATION-CAPABLE VEHICLES, 25,000 VEHICLES PER RUN)

Mean Value	***ST-model***	***Estimation model***
MAPE	2.06%	2.62%
MAE	1.28	1.64
RMSE	1.76	2.25

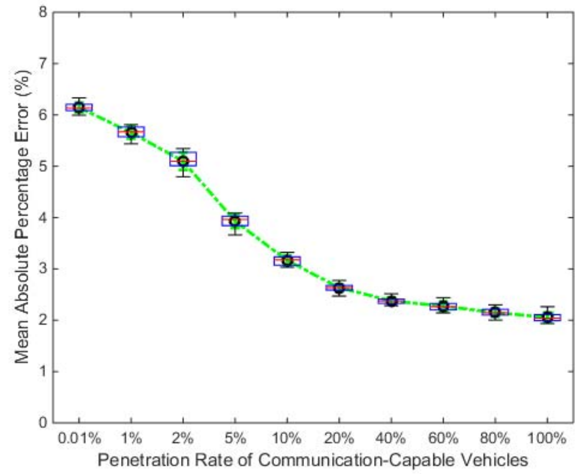
In Fig. 9(b), it can be observed that the travel time (median) decrease is quite stable as the penetration rate increases (starting from 10%), which can be still more than 5% even when only 10% vehicles on road could supply their information for the traffic state prediction. Using the one-way analysis of variance (ANOVA) as the statistical analysis method, we conduct statistical analysis for the last seven group data (i.e., 5%, 10%, 20%, 40%, 60%, 80%, and 100%) of different levels of penetration rate. The result of a rather big p-value 0.81 (which is >0.05) indicates that the means between the seven groups are not statistically significantly different from each other. The p-value turns out to be small (0.02) when the 2% penetration rate case is added into the analysis. Therefore, we conclude that there is no significant difference in travel time improvement, when penetration rate of communication-capable is higher than 5%, due to relatively sufficient information.

Moreover, to better assess the benefits of the ST-model, the forecast accuracy (MAPE, MAE and RMSE) of both the ST-model and basic estimation model (see Equation (5)-(7)) are compared (see Table IV). It can be seen that the accuracy of the proposed ST-model outperforms the basic estimation model in every aspect.

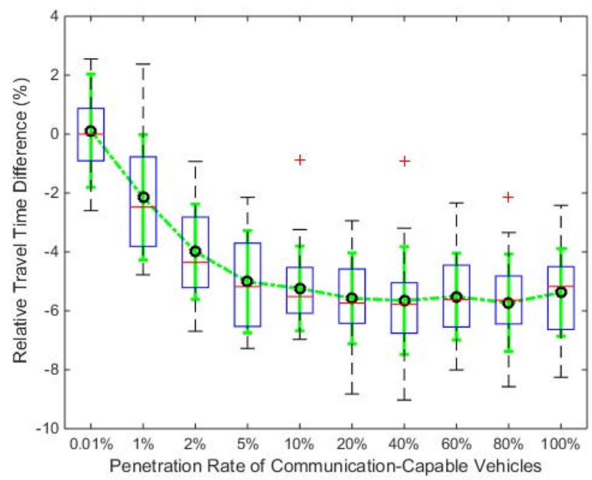
c) Sensitivity analysis on information update cycle: Besides traffic demand and penetration rate, the N-min information update cycle may also have impacts on the proposed application performance. Whereas, what is different with the other two factors (traffic demand and penetration rate, whose impacts on the traffic time decrease are relatively pure) is the information update cycle has more combined impacts.

As displayed in Fig. 10(a), the longer information collection duration/information update cycle (i.e., the lower information update frequency) leads to higher prediction accuracy. To be specific, the 5-min case has better MAPE than 1-min case as it aggregates the results of five 1-min error, i.e., $\left|\sum_{i=i}^{N} x_i\right|/N \le \sum_{i=i}^{N} |x_i|/N$, which could clearly explain the MAPE results in Fig. 10(a).

From Fig. 10(b), we observe less relative travel time decrease (median) is achieved as the information update cycle gets longer, even though the corresponding MAPE gets smaller. Due to the longer information collection process, the lane change recommendation generated from the proposed application is less frequent. Simultaneously, due to the lagged real-time lane change guidance, it can be expected that the corresponding lane-changing operation number induced by the proposed application drops as well, leading to weakened application performance in terms of travel time decrease.



(a)

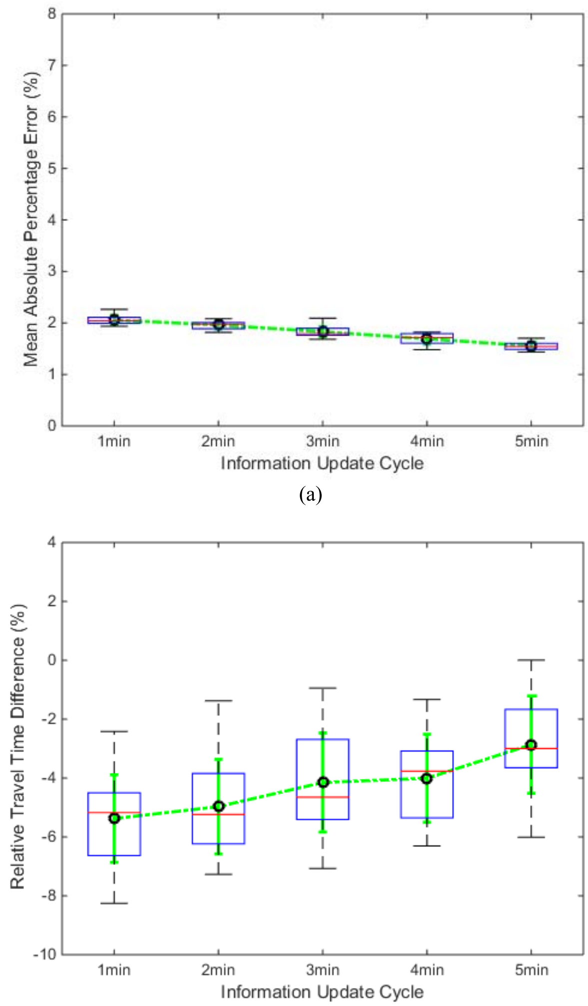


(b)

Fig. 9. Measures of effectiveness for different penetration rates of communication-capable vehicles. (a) Mean absolute percentage error. (b) Relative travel time difference.

In addition, the 5-min cycle might not be a better "resolution". For example, during one 5-min cycle after one prediction is made, the target vehicle follows the optimal lane sequence obtained from the previous 5-min prediction results. The number of prediction generated by the proposed application can be only 1-2 during the whole trip at the 5-min update cycle. Actually, the traffic status of lane-level speed change even at every one minute. On the contrary, 1-min cycle can provide the target vehicle the more up-to-date information used for updating the micro-routing. In other words, the chances of application-equipped vehicles staying at the correct target lane of the current time, is increased due to the timely information update.

3) Safety Performance Analysis: Moreover, to evaluate the safety performance of the proposed application, we analyzed the risk index in terms of the potential conflict frequency (mentioned in Section V.B.1).b)) using SSAM software [57]. The potential conflict frequency results (there are ten simulation runs for each result) are summarized in Table V.



(a)

(b)

Fig. 10. Measures of effectiveness analysis for different information update cycle. (a) Mean absolute percentage error. (b) Relative travel time difference.

There are slightly higher lane changes induced by the proposed application, however, the potential conflict frequency is lower than the baseline. There are several reasons: 1) The restriction strategy on extra lane changes within one lane/road segment prevents the application-equipped vehicles from performing too frequent lane changes; and 2) only adjacent lane changes are allowed in the proposed application within N-min, which helps reduce conflict risk as well.

VI. Discussion and Future Work

Based on predicted lane-level traffic states enabled by CV technology, a CV application called Lane Selection Assistance Application is proposed in this paper. This application can help drivers choose a relatively faster travel lane at any point in time. The results can be summarized as: 1) the ST-model outperforms the basic estimation model in terms of traffic state prediction accuracy; 2) for all the scenarios simulated in this study, the lane selection assistance application does help the application-equipped driver reduce travel time, compared with the baseline case (i.e., normal driving without any assistance); 3) results of traffic volume sensitivity analysis indicate that the proposed application can provide travel time benefits under various congestion levels. Travel time improvements can be observed even under heavy traffic condition (i.e., LOS E (unstable flow), or 32,000 vehicles/run); 4) the proposed application performs robustly and can be effective even in an early deployment of CV technology with relatively low penetration; 5) different information update cycles have combined impacts on the travel time improvements. Higher travel time improvements can be achieved if the real-time state information of on-road vehicles is updated more frequently; and 6) the potential conflict risk of application-equipped vehicles is reduced as well, due to the more strategic and informed lane changes suggested by the proposed application.

TABLE V

The Mean Actual Lane Change Number and Potential Conflict Frequency for the Proposed Application (100% Penetration Rate of Communication-Capable Vehicles, 25,000 Vehicles per Run) and the Corresponding Baseline

Mean Value	***Baseline***	***5-min info cycle***	***1-min info cycle***
Lane change number	3.64	4.42	4.96
Potential conflict frequency	0.1446	0.0879	0.0800

Furthermore, it should be noted that more advanced models can be explored in the future to better predict the lane-level traffic states. Adding the Markov chain theory and the Adaptive Smoothing Method [58] to the proposed model is another interesting future work. In addition, further tests on the impacts of key spatial-temporal related parameters remain as future research topics. Moreover, since this application can help vehicles in the traffic stream obtain mobility benefits in terms of travel time reduction, unintended issues (e.g., oscillations in lane changes) might happen if a significant number of vehicles use this application independently and simultaneously. This will lead to the necessity of considering a priority strategy, arbitration mechanism, or optimization methods of vehicle groups in future work. Furthermore, to test the effectiveness in a more comprehensive way, it is also necessary to consider a more realistic driver behavior model, e.g., based on real-world human drivers' experience about which lane and when to change lanes to achieve a higher speed [59]. In addition, as a step towards the potential real-world test, one way is the "hardware-in-the-loop" where one or two real vehicles represent the model in the simulation and interact with other vehicles in the microscopic simulation.

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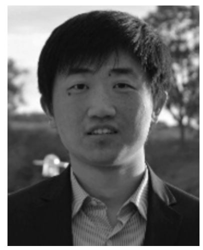

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