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Iterative Markov Chain Future Speed Prediction with Connected Vehicle technology

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Summary

As part of the predictive energy optimization for Plug-in hybrid electric vehicles (PHEV), future speed prediction model has been proposed by combining Markov chain and iterative model with driving style identification. Having generated transition probability matrices (TPM) from history driving data in an offline calculation, the future road is segmented given a route selected by a driver. Future speed is predicted from TPM iteratively to meet criteria from road segmentation.

The developed future speed prediction can be also used for different applications: distance-to-empty (DTE) estimation for battery electric vehicles (BEV), shifting optimization for automatic transmission and trip duration estimation for a navigation system.

Keywords: connected, navigation, prediction, optimization

1 Introduction

Electrified vehicles have been expanded their market at unprecedented speed. Toyota and United States were the main enablers for electrified vehicle until around 2010. Toyota was a very first company, which made a huge success with hybrid electric vehicles, Prius, and open electrified vehicles market with expanding its technology to all the lineup. The United States, especially California, has implemented tax credits for electrified vehicles to compensate their high price compared to conventional vehicles [1]. Since 2010, the Chinese government is driving battery electric vehicles (BEV) market with high incentive to mitigate the emission problem in the city, and European original equipment manufacturers (OEMs) have been starting to focus on electrified vehicle technology since diesel scandal in 2015 whereas they had favored diesel engine over electrified vehicles until then [2].

The other important trend in automotive sector these days is an autonomous and a connected vehicle. There has been an argument when autonomous vehicles (AV) will be penetrating to the market, but it cannot be denied that AV promotes the investment to infrastructure for the connected vehicle. On top of investing infrastructure, the advanced map, so call ADAS electric horizon (ADAS e-Horizon) has been enhanced [3], this advanced map is a key enabler for future speed prediction, which can be used for predictive control of the electrified vehicles.

There are three main applications of future speed prediction: trip duration calculation, distance-to-empty (DTE) estimation for BEV, and predictive control for energy management of HEV/PHEV. Navigation unit on vehicle needs to calculate time to the destination, and speed prediction is a key to calculate trip duration. However, average speed prediction rather than time-series speed prediction is enough to its calculation. Another application of speed prediction is DTE estimation for BEV. Even though DTE is calculated for the conventional vehicle to indicate the remaining distance for refueling a car, it is particularly critical for BEV due to its range anxiety. If future speed is available the requested wheel energy can be calculated, consequently, more accurate DTE calculation for BEV is possible.

The model predictive control needs to have a time-series speed profile for a given cycle to calculate request wheel torque. While the model prediction control (MPC) requires predicting future speed for short time window, global optimization approach, for instance using dynamic programming, needs the cycle-length speed prediction. Predictive energy optimization for the electrified vehicles can improve fuel consumption and emissions with speed prediction as the battery provides more room to optimize the controller.

The proposed speed prediction model is the iterative Markov chain with driving style identification (DSI) and road segmentation for the entire journey. The limit of using only empirical modelling (e.g. Markov chain or Neural Networks) is that its prediction is based on the past information as history data itself defines the model. The history data managed to give a hint for predicting future speed, and yet the error between prediction and real speed is inevitable due to the uncertainty of the real world. The future information on the road is more important to anticipate the future since it reflects near-future status. In order words, static information from advanced GPS, (e.g. speed limit, traffic light, traffic sign and congestion) can tell more about future speed than past speed data for the cycle-length speed prediction. The previous study by Karbowski et *al* [4] is using the future itinerary information (e.g. road sign, average speed) for speed prediction.

In this study, future speed prediction is based on both history data (past), and route information (future). As drivers tend to follow their driving habit, history data contains dynamic information of future speed prediction. Based on the history data, a statistical model (e.g. Markov chain) can be built, which contains a probabilistic matrix for the transition from current status to next one. On the other hand, driving speed can be varying depending on the road situation, such as traffic congestion, speed limit and traffic sign. These road information define the average speed of a vehicle, as a driver tends to follow speed limit and speed of congestion. As both history data and route information are significant to predict speed, they are combining in an iterative way. In the end, future speed profile will be compared with test results and analyzed in terms of positive driving energy.

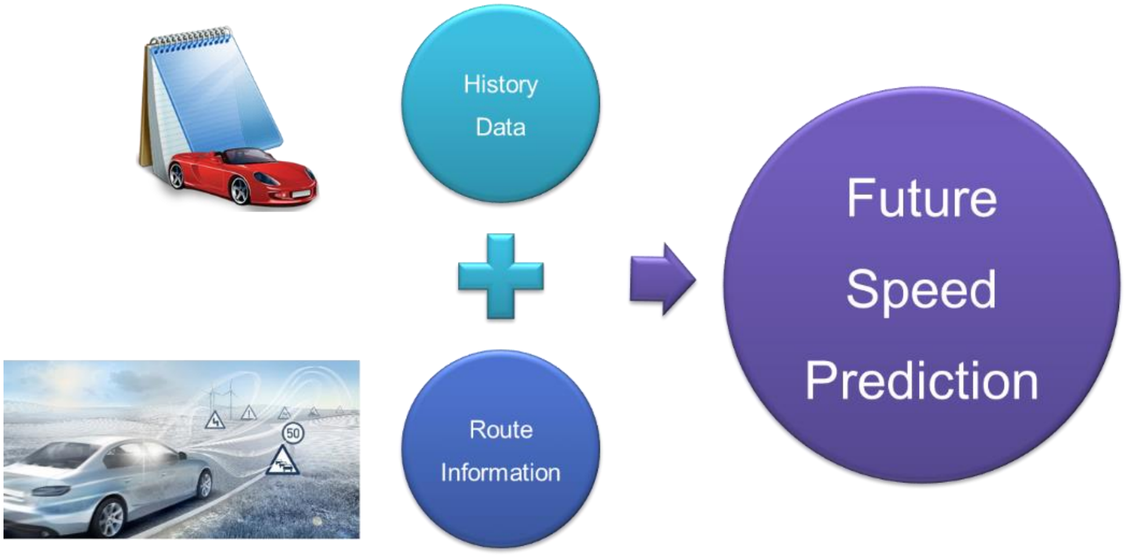

Figure1: Future speed prediction structure

2 Literature Review

There are two categories of speed prediction: parametric and non-parametric speed prediction [5]. A parametric speed prediction is a model-based approach, meaning that a model is necessary to be defined first and is trained with the test data. The examples of parametric speed prediction are constant speed or acceleration model [5], intelligent driver model [6] and auto-regression model [7]. On the other hand the non-parametric speed prediction, or empirical modelling, is a data-driven approach, which requires less effort to define a sophisticated model beforehand but requires the larger set of data to define its model. Markov chain [8] and Neural Networks [9] are widely used for a non-parametric approach for speed prediction.

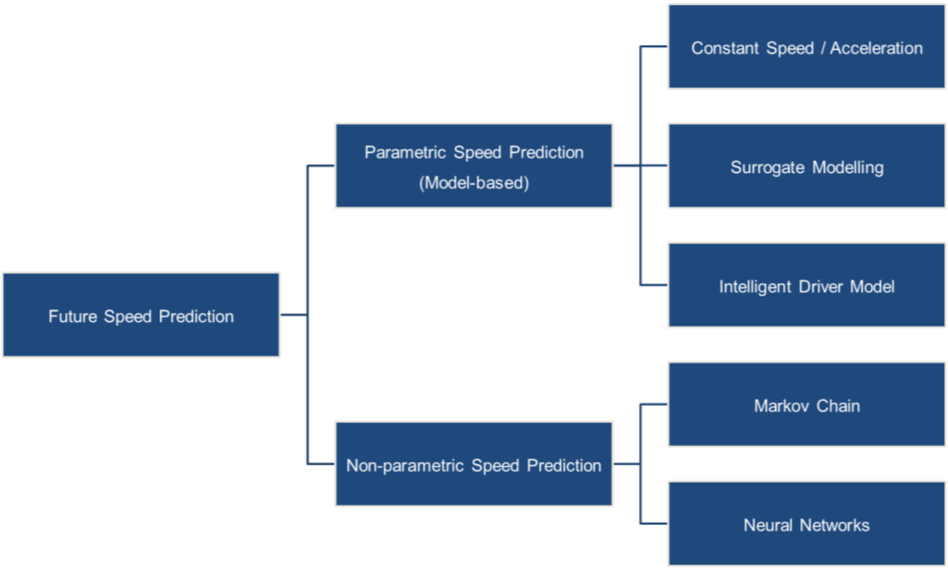

Figure2: Future speed prediction summary

The constant speed and acceleration models assume that the ego-vehicle keeps its current speed or acceleration for next state, and they are popular for a short-window speed prediction like collision prediction when no environment information is available. And the Surrogate modelling (SUMO) and Intelligent Driver Model (IDM) predict the speed of the ego-vehicle by taking into account interaction with the traffic. While SUMO is based on the “safe distance” between the ego-vehicle and the vehicle in front, IDM is based on the “desired distance” between them [5].

The parametric speed prediction models have been prevalent until recently because they are required less training data compared to the non-parametric speed prediction and are well-understood as they are white box models. The non-parametric speed prediction models are getting attention recently thanks to the advance of connected vehicle technology. Neural Networks and Markov chain are most popular choices among non-parametric models. Neural Networks (NN) is a powerful algorithm for time series forecasting like weather forecast and stock market prediction. And depending on the number of layers and neurons, the nonlinearity of the system can be modelled. Markov chain is based on the transition probability from the current state to next one. There are different orders of Markov chain depending on the number of past data considered. For example, if next state $x(t+1)$ is determined from current state $x(t)$ it is one-stage Markov chain, and if next state $x(t+1)$ is determined from current state $x(t)$ and the previous state $x(t-1)$, it is called two-stage Markov chain. The higher order of Markov chain the more past information can be taken into account, but it requires larger size of data [5].

While the parametric speed prediction needs to define a model based on road information, the non-parametric speed prediction needs a large set of data rather than a model. As it is a challenge to record big data in the internal system of a vehicle at the moment due to the limit of memory and computation power, the parametric speed prediction has been a plausible solution for a vehicle application, but the non-parametric speed prediction is becoming applicable thanks to the connected vehicle technology. In this study, non-parametric model (Markov chain) is combined with a parametric model (iterative model) to compensate the pro and con of each model.

3 History Model – Transition Probability Matrix

3.1 History Data Collection

Markov chain requires a large set of data, which should cover most of the user case to guarantee a statistical meaning. And since in this study data is categorized by different driving style, road type and event it requires even larger data set. Data is collected from city, rural and highway cycles for about 400 hours of trip duration with 100 ms sampling time. For each micro-trip, from vehicle launch to next standstill, driving style and road type are evaluated and each driving events (e.g. launch, cruising and deceleration) are determined based on vehicle speed and acceleration. Afterwards all the data are categorized based on driving style, road type and driving events and are discretized to 0.5km/h and resampled to 1 second. The number of transition from one speed and acceleration state to another are counted, and 27 transition probability matrices are generated.

Table1: Customer data summary

Driving Style	Road Type	Total Duration [hrs]	Total Distance [km]	Total Number of Trip [-]
Calm	City	51.9	1,271	3,036
	Rural	27.9	1,186	741
	Highway	28.0	2,210	134
Normal	City	33.4	933	1,868
	Rural	51.0	2,426	1,482
	Highway	192.6	17,897	839
Aggressive	City	0.7	19	58
	Rural	3.9	193	155
	Highway	11.1	1,051	73

The summary of customer data in terms of duration, distance and the number of trips has shown in Table 1. Markov chain needs to have enough transition, total duration is significant for Markov chain as it is directly related to the number of transition. For driving style, the portion of aggressive is ~3.9% since the data was recorded from a limited number of customers. 69.2% of total duration are categorized as normal driving style, and 26.9% as calm driving style. Due to this limitation, in this study, normal driving style is used for future speed prediction.

3.2 History Data Processing

Customer data was processed with DSI, road type and event recognition algorithms, which were part of previous research [10]. DSI algorithm is to assess the level of aggressiveness from a statistical analysis with vehicle data (e.g. vehicle speed, acceleration pedal). As road type (city, rural, and highway) and driving events (accelerating, cruising, and braking) requires the different models for DSI, road type and driving events are first assessed as a part of DSI model. From the analysis, the relationship between average speed and stop frequency shown in Figure 3, road type is categorized into city, rural and highway depending on its inclination between average speed and stop frequency. Vehicle speed threshold between city and rural is 35 km/h and between rural and highway 70km/h.

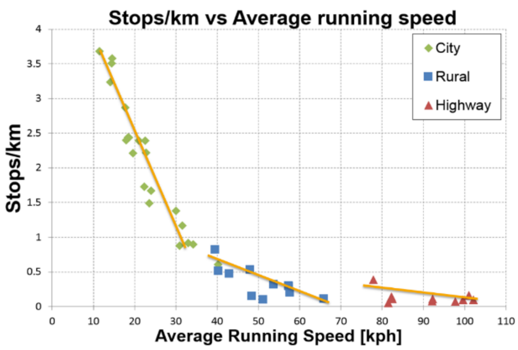

Figure3: Road type determination based on vehicle speed [10]

Driving event is defined with vehicle speed and acceleration, and there are four driving events as shown in Table 2: accelerating, cruising, decelerating and stop. Due to the signal processing issue, there can be one point for certain event, which is not necessary for TPM since the transition of vehicle speed within the same event is needed for TPM. Hence, one point event is interpolated with the previous event.

Table 2: Driving event recognition threshold

Driving Event	Vehicle speed (km/s)	Acceleration (m/s^2)
Accelerating	V >= 1	a > 1/3.6
Cruising	V >= 1	-1/3.6 <= a <= 1/3.6
Decelerating	V >= 1	a <= -1/3.6
Stop	V < 1	-

3.3 Transition Probability Matrix

A Markov chain is the type of process that the outcome of a given state can affect the outcome of the next *state*, and the transition from a given state and the next state is defined by transition probability matrix, which is derived from test data. A *step* is each move from one state to the other state, and given a set of state, s = {s_1, s_2, ... , s_r}, the transition probability from s_i to s_j is p_{ij}. Transition probability matrix, S, is a full matrix of transition probability from one state to another state [11].

For speed prediction, the state is defined by vehicle speed and acceleration in this study, and the state and transition probability can be expressed as below:

$$s_i = (v_i, a_i) \tag{1}$$

$$p_{ij} = P\big(s_i \to s_j\big) = P\big[(v_i, a_i) \to \big(v_j, a_j\big)\big] = \frac{N(S_i \to S_j)}{\sum_{n=1}^{n=r} N(S_i \to S_n)} \tag{2}$$

Where v indicates vehicle speed, a longitudinal acceleration, P refers to the probability, N the number of transition. Next acceleration is not determined by the transition probability, but derived from selected vehicle speed difference and sample time.

Suppose the current state is 10 km/h and 0.5 m/s^2 and there are five data points for the next state from history data as shown in Table 3. The total number of transition ($\sum_{n=1}^{n=r} N(S_i \to S_n)$) is five in the example, and the transition to particular state (12km/h) is two ($N(S_i \to S_j)$), thus the transition probability from (10 km/h, 0.5 m/s^2) to (12km/h) is 0.4. Therefore, when predicting future speed with this TPM, if the current state is (10 km/h, 0.5 m/s^2), the chance to select 12 km/h as a next state is 40%.

Table 3: Transition probability matrix example

<table>
<tr><th>Current State</th><th>Next State</th><th>Number of Transition</th><th>Probability</th></tr>
<tr><td rowspan="5">(10km/h, 0.5 m/s2)</td><td>8 km/h</td><td>1</td><td>0.2</td></tr>
<tr><td>10 km/h</td><td>1</td><td>0.2</td></tr>
<tr><td>12 km/h</td><td rowspan="2">2</td><td rowspan="2">0.4</td></tr>
<tr><td>12 km/h</td></tr>
<tr><td>15 km/h</td><td>1</td><td>0.2</td></tr>
</table>

In this study, 27 TPMs are generated for three different road types (city, rural and highway), three different driving styles (calm, normal, and aggressive) and three different events (acceleration, cruise and deceleration). It is important to use enough size of data, otherwise, Markov chain cannot select the next state from TPM. In order to check the coverage of data for each TPM, the density of vehicle speed and acceleration are plotted in Figure 4 for each driving event. While vehicle speed range up to 100 km/h for all of them, acceleration distinguishes accelerating, cruising, and decelerating: accelerating cover from -1 ~ 4 m/s^2, cruising -1 ~ 1 m/s^2, decelerating -4 ~1 m/s^2. The noticeable thing is that for decelerating there is high density around vehicle speed 40 km/h and -0.4 m/s^2, which corresponds to the tip-out scenario before pressing braking pedal. And cruising event shows high density around zero acceleration. When these TPMs are used for Markov chain, cruising TPM is more likely to keep zero acceleration and decelerating TPM provides slight negative deceleration before braking to represent the tip-out events. Even though these TPMs are big enough to cover speed-acceleration area, the transition between two events could cause a problem due to missing points. The method to overcome this problem will be discussed further in next chapter.

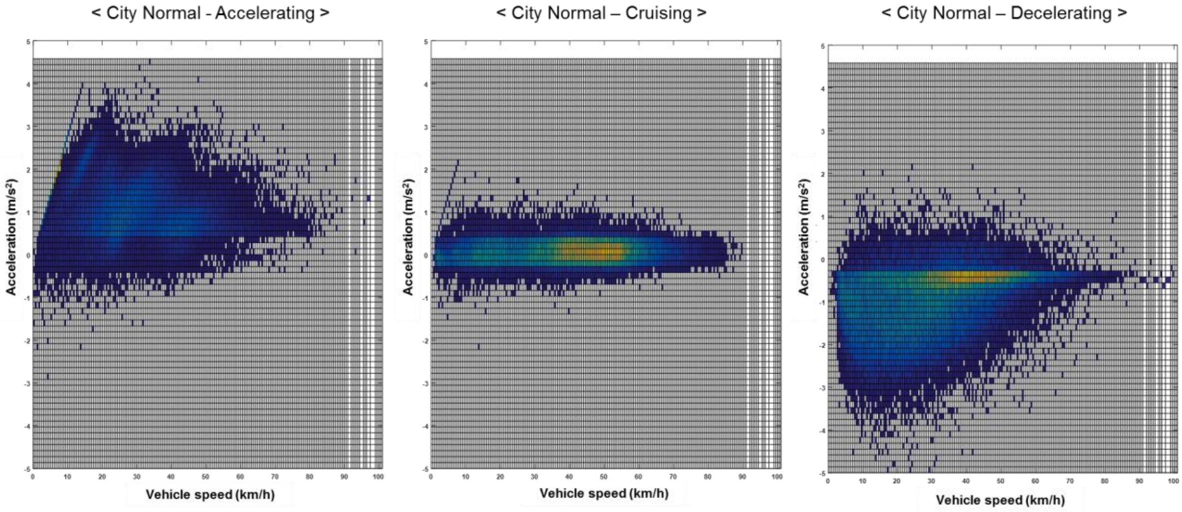

Figure4: Transition probability matrix comparison

4 Future Model – Road Segmentation

4.1 Road Data Collection

Road data is necessary to obtain the necessary road information from the advanced navigation for the selected routes. Advanced Driver Assistance Systems Interface Specification (ADASIS) is an industry standard interface to access the ADAS Horizon, which is enhanced navigation information to improve ADAS features. The ADASIS is to define an open standardized map data model as well as interface specification to provide ADAS Horizon data [13]. Whereas ADASIS is mainly for ADAS applications, it can be used to adapt the controller of electrified vehicles given an itinerary. Among the signals from ADASIS, the required signals for future speed prediction are selected as in Table 4. For instance, speed limit, stop sign, and traffic light are significant for the speed prediction as they constraint speed range, and even though other signals, like a curve, give-way, grade-down, and traffic queues sign have an impact on future speed too, they are not considered due to their rarity in the real-world cycle. For the speed prediction development, speed limit, stop sign, traffic light and the end-of-speed limit sign has been recorded for selected routes.

Table 4: Signal list from advanced GPS [13]

Traffic sign or situation	Description	Priority for speed prediction
Speed limit	Vehicle speed limit	1
End of speed limit	End of current speed limit, default speed limit is used afterwards	1
Stop sign	Vehicle stop sign	1
Traffic light	Traffic light location and schedule for red, green and yellow in time	1
Bend left / right	Curve to left or right	2
Double bend left / right	S curve to left or right	2
Give way sign	Yielding to other vehicles	2
Grade down sign	Downward hill	2
Traffic Queues	Traffic queue likely	2

4.2 Road Data Processing

Once a driver selects an itinerary in advanced GPS, the road information for the itinerary will be collected from the map database. Speed limit, stop sign and traffic light are used for the road segmentation. Stop sign and speed limit change are the boundary for road segmentation. And traffic light is also considered based on its schedule in that the probability of red light is based on time ratio of red light out of total time. Suppose that the schedule for the traffic light is 5 sec, 1 sec, 5sec for red, yellow and green respectively. The chance to encounter green light is 0.45 from the red light duration (5 sec) divided by total duration (11 sec). As traffic light status needs to be predicted at the beginning of a journey, it is inevitable to avoid the error but it is plausible to use the chance based on the traffic light schedule. If the vehicle to infrastructure (V2I) communication is available, the traffic light status can be updated as the vehicle is approaching it: the accuracy of prediction would be improved.

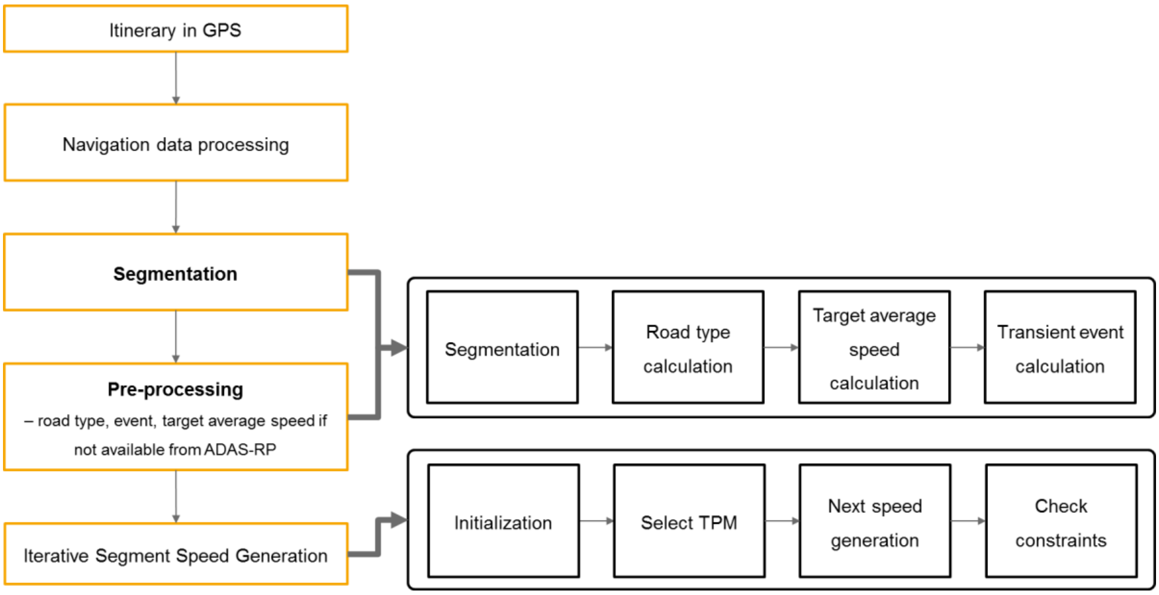

Figure5: Iterative Markov chain speed prediction process

If the traffic light is predicted as red light, it can be the boundary of the road segment, which means vehicle speed is most likely to be zero on that point. Sub-segmenting is carried out based on the driving events, meaning that accelerating is determined until vehicle speed reaches to the speed limits for launching and speed limit increase, for example. And road type (city, rural, highway), which is necessary to select different TPM, are calculated based on the speed limits for each sub-segment. Target average speed for each sub-segment, which is necessary to define criteria for iterative Markov chain model, can be also calculated from speed limit and driving style.

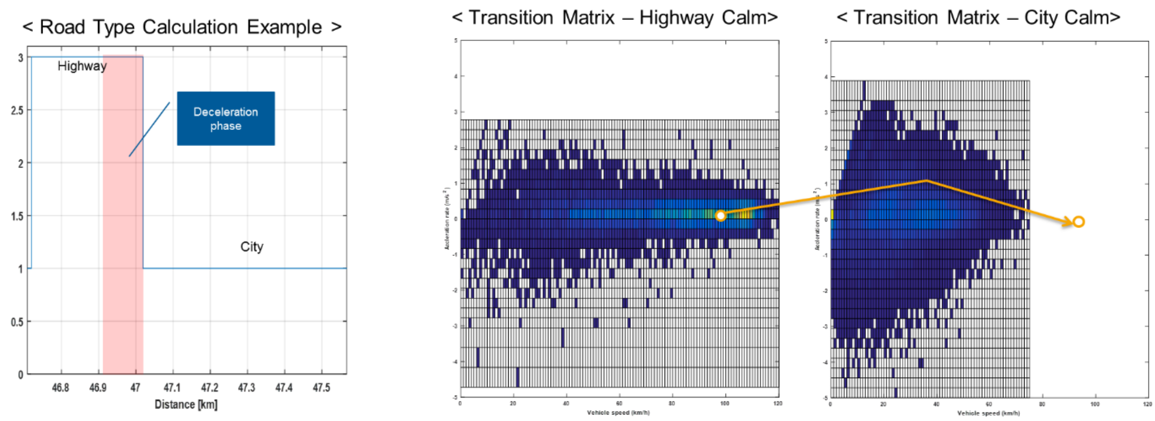

Figure6: Transient event example

The transient event (e.g. stopping, braking) when approaching the stop sign or speed limit change, is defined for selecting different TPM in the same sub-segment. When the road has changed from highway to city, for example, TPM needs to be selected accordingly. And as the speed range for highway is wider than the city, there is a case when the current state in city TPM is empty if the vehicle speed is high. Therefore it is necessary to have the transient region between two different road types, and in this case, braking event is added to reduce vehicle speed before the city cycle, and then braking TPM, which has a high chance of deceleration, will be used when generating future speed. This approach does correspond with the real driving situation since a driver tends to reduce vehicle speed before exiting the ramp of highway.

4.3 Iterative Markov Chain

Markov chain speed prediction is to populate future vehicle speed based on TPMs generated from test data. Based on the transition probability, the most likely next state is selected. The problem of Markov chain to predict vehicle speed is that it is purely based on input data, and it can cause a problem for low speed because it is likely to have similar probability for acceleration and deceleration. Suppose that there is one history data with one acceleration and one deceleration event. When TPM is generated from this test data, for one state (e.g. 10km/h) the chance for the acceleration and deceleration are same, which means that when generating speed for 10 km/h state with this TPM the acceleration and deceleration can happen with same chance. This causes a problem of busy fluctuation in low-speed prediction. This is an inevitable problem of Markov chain speed prediction.

In order to resolve the problem aforementioned, the driving events need to be taken into account with Markov chain because after launching a vehicle it is more likely to keep acceleration until reaching to speed limits unless something has happened. It is similar to braking event as s vehicle tends to keep deceleration from current speed to zero when approaching to the red light or stop sign. In this way, the driving event can be defined and different TPM can be used accordingly. This approach does match with the driving scenario as a driver tends to keep one's driving event for certain period. And the other way applied is Iterative Markov chain with certain criteria. The criteria can be average speed, speed limits, length (distance) of the segment [15]. In this study, the criteria are defined in road segmentation, and then Markov chain is run iteratively until all the criteria are met. The speed limit, target distance, average vehicle speed and final speed for sub-segment are criteria to meet.

5 Results & Analysis

To compare the future speed results and the real vehicle speed, two routes are selected and 30 future speed profiles are generated from iterative Markov chain model. Since the Markov chain is a statistical model its results cannot be identical, so empirical cumulative distribution function (ECDF) are used to see the results. Average vehicle speed, average absolute acceleration and positive driving energy are chosen as the metrics for the comparison. Total positive energy is one of the significant parameters as it is directly related to fuel economy of HEV or PHEV, battery usage for electrified vehicle and consequently DTE for battery electric vehicle.

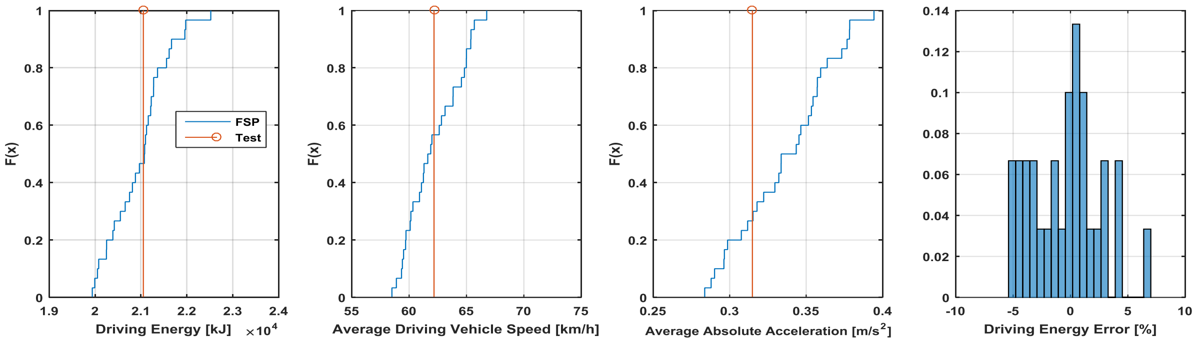

Figure7: Speed prediction results

For the average vehicle speed, test result shows 62 km/h, and the speed prediction ranges from 57 to 67 km/h. And in terms of the average absolute acceleration, while the test result shows 0.32 m/s^2, the speed prediction results are from 0.28 to 0.39 m/s^2. When it comes to the positive driving energy, the test result is approximately 21,000 kJ, and the speed prediction has ±5% error compared to test results. As shown in Fig 9, the high-density region is similar between test and speed prediction model: vehicle speed 80 ~ 100 km/h and acceleration -0.5 ~ 0.5 m/s^2. However, future speed has more point high absolute acceleration, meaning Markov chain can have more dynamic in low speed because it is more likely to have fluctuation because acceleration and deceleration are treated equally.

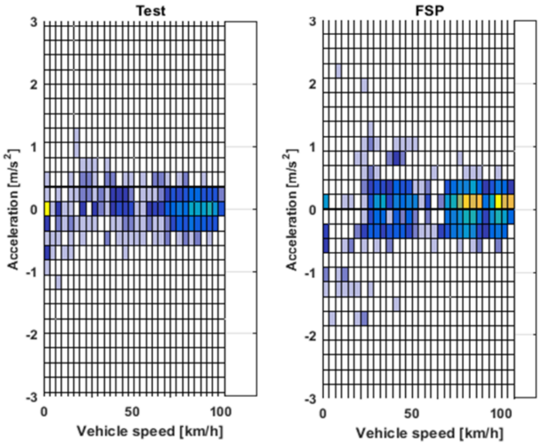

Figure8: Speed and acceleration residency comparison

Even though the positive driving energy is an critical factor with regards to vehicle applications as aforementioned, its error is inevitable especially for the high-speed region. Because driving energy is a function of the vehicle speed cubed and consequently, the speed error is exaggerating in driving energy term.

$$Driving\ Energy\ (E_{Drv}) = \int_0^{t_p}(F \times v)dt = \int_0^{t_p}\left(av + bv^3 + mv\frac{dv}{dt}\right)dt \tag{3}$$

Where a is the rolling drag (N), b is air drag coefficient and m is a mass of the vehicle. And when vehicle speed is constant (v_c)

$$Driving\ Energy\ (E_{Drv}) = (av_c + bv_c^3) \times t_{tot} \tag{4}$$

Where t_{tot} is the total time duration. And driving energy error can be expressed with speed prediction error.

$$Driving\ Energy\ Error = \frac{Driving\ energy\ of\ Prediction}{Driving\ energy\ of\ Real} = \frac{(av_c' + b\,v_c'^3)\times t_{tot}'}{(av_c + bv_c^3)\times t_{tot}} = \frac{a + b\cdot e^3 \cdot v_c^2}{a + b\cdot v_c^2} \tag{5}$$

Where v_c is the real speed,v_c' is the predicted speed, e is speed error between real speed and predicted one.

Therefore the higher vehicle speed is the more error in terms of energy is. This is the limit of cycle length speed prediction for the predictive controller of HEV/PHEV and DTE calculation of BEV.

6 Conclusions

In this study, the iterative Markov chain speed prediction is developed in a way to take the past and future information into account at the same time. The Markov chain is a way to consider past event as TPM is generated from history data, and the iterative model is a way to consider future information with road segmentation. On top of that, in order to take into account the driver's characteristic, the driving style is newly considered as a part of TPM. In the end, 27 TPMs for three driving styles, three driving events and three road types are generated for Markov chain model.

The developed model is compared with speed profile from vehicle test in terms of the average speed, average absolute acceleration and positive driving energy. As Markov chain is a statistical model 30 predicted speed are created and they show similarity with test vehicle speed in terms of average speed and average acceleration, and their error in terms of positive driving energy is ±5%. Even though the error between prediction speed and real speed is inevitable for cycle length speed prediction its accuracy can be improved with additional information sources such as the vehicle to infrastructure (V2I) and vehicle to vehicle (V2V) communication, which is researching intensely for autonomous vehicle development at the moment.

As a next step, other information (e.g. traffic density, roundabout, curve etc.) is necessary to take into account in order to improve the accuracy of speed prediction. To do so it is necessary to understand the relation between vehicle speed and each case from customer data. And one of the challenges of iterative Markov chain is computation time, because it iterates many times until all of the criteria are met, and therefore computation time needs to be optimized for vehicle implementation for the future.

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