# Distance Constraint Model for Automated Lane Change to Merge or Exit

**Quoc Huy Do*, Hossein Tehrani**, Masumi Egawa**, Kenji Muto**, Keisuke Yoneda*, Seiichi Mita***

**Research Center for Smart Vehicles of Toyota Technological Institute, 2-12 Hisakata. Nagoya, 468-8511, JAPAN (Tel: +81-52-802-1822; e-mail: { huydq,yoneda,smita }@ toyota-ti.ac.jp)*
*** Corporate R&D Div.3, DENSO CORPORATION, 1-1, Showa-cho, Kariya-shi, Aichi-ken, 448-8661, JAPAN (Tel: +81-566-25-57558; e-mail: {hossein_tehrani, masumi_egawa, kenji_Muto}@ denso.co.jp).*

Abstract: Lane change is a complicated maneuver and that causes many severe highway accidents. Automatic lane change has great potentials to reduce the number of accidents. Previous researches mostly tried to find an optimal trajectory that can be applied for simple lane change. They do not consider time/distance constraints for doing the lane change during the merging/exiting. Through analysis of human driver lane change data, we propose a multi segments behavior and motion model to mimic the human driver operation. We developed a simulation platform in PreScan and evaluated the proposed automatic lane change model for challenging scenario in the merging/exiting.

*Keywords:* Automated Guided Vehicle, Autonomous Control, Driver Models

## 1. INTRODUCTION

Statistical data of highway traffic accidents shows the human error is a major reason for about 90% of accidents (Volvo 2013). Lane change manoeuvre is a cause for many severe highway accidents due to wrong estimation of surrounding environment or wrong manoeuvre. Currently, ADAS or automated driving proved their great potentials to reduce the impact of human errors through providing warning, semi or fully automated solutions. Previous researches in fully automated driving systems designed for lane change or overtake manoeuvres, can be divided into rule-based (Fletcher, et al., 2009), or utility-based (Dolan & Litkouhi, 2010), approaches. The lane changing trajectory is generated according to the vehicle states, surrounding vehicles and road information, and then the control laws are designed to use on-board sensors to track the generated trajectory.

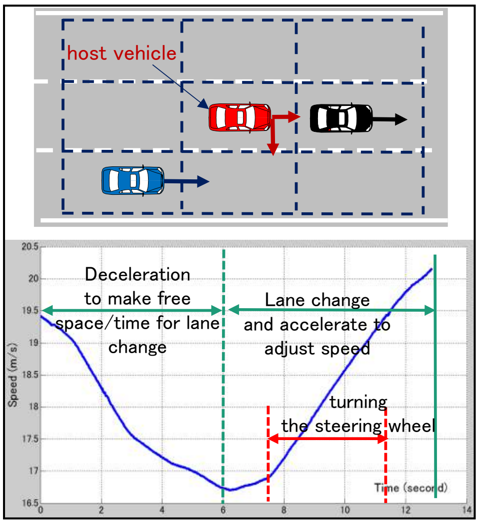
In (Kasper , et al., 2014), authors introduce an object-oriented Bayesian network approach for traffic scene modelling for lane change manoeuvres detection. Bayesian network was also used by Schubert et al (2010) for lane change situation assessment and decision making. Other related researches focus on manoeuvre prediction. In (Friedman et al., 2009) authors trained Bayesian belief networks for the prediction of lane changes. A dynamic Bayesian network is also used by Gindele et al. (2012) for behaviour and trajectory prediction. The fuzzy logic was used by Naranjo et al (2008) for solving the modelling lane change decision making problems. They use fuzzy controllers that mimic human behaviour and reactions during overtaking manoeuvres. Simon and Markus (2013) applied an online Partially Observable Markov Decision Process to solve the decision making for lane change. Brechtel et al (2011) apply probabilistic MDP-Behavior planning for cars. Ardelt et al (2012) presented a probabilistic approach to build a lane change framework for automated vehicle. In (Jula et al., 2000) presented the collision avoidance by analyzing the kinematic of the vehicle then calculated the minimum safety space requirement for doing the lane change. However, they provided a more general framework rather than focusing on lane change decision situations in particular.

Most of discussed researches try to predict the behaviour of surrounding vehicle or are based on the kinematic functions and try to find an optimal trajectory for lane-changing (Ziegler et al., 2014). They ignore the host vehicle lane change behaviour model for complicated scenarios or in the presence of time/distance constraint for merging/exiting of the highway. To exactly understand the human lane change model, we have conducted lane change experiments at Japan highway. The results of the human lane change motion analysis already published by the authors (Tehrani et al., 2014). Through analysis of human lane change data including neighbour vehicles and motion/behaviour data, we realized that the human model is not a single stage. In this paper, we propose a multi segments behaviour and motion model to mimic the human driver lane change operation. At “behaviour segment”, the host vehicle tries to adjust the longitudinal distance, position or relative velocity to make or find suitable free space in front and the destination lane. At “motion segment”, the host vehicle starts lateral motion and enters into the destination lane. The proposed method is able to solve and generate solution a for complicated lane change scenario.

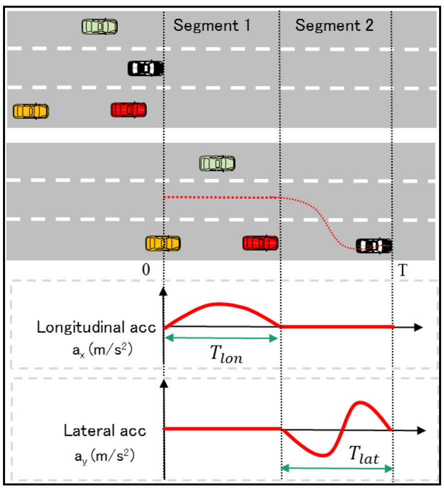
The structure of this paper is as follows; Section 2.1 explains our automatic vehicle’s lane change flowchart. Section 2.2 introduces our scenario modelling approach. The behaviour decision and velocity planning are presented in section 2.3 and 2.4. The lane change motion planning is described in section 2.5. Section 3 presents our simulation for merging in and exiting situation. Finally, the conclusion is given in section 4.

## 2. LANE CHANGE MODEL

Through experiments, we learned that the human driver model is not just the turning of steering wheel and it starts at seconds before the steering. As shown in Fig. 1 (a), turning the steering wheel starts at time 7.6 thought the human driver has already started to decelerate and reduce the vehicle speed from 19.5 m/s to 16.7 m/s. We see the driver has to decelerate to keep safe space from the front vehicle (black vehicle) and wait to let the blue vehicle to pass it. In this paper, we propose a two-segment behavior/motion lane change model as shown in Fig. 1 (b). In segment 1, the driver adjusts the longitudinal speed and makes safe space based on the positions and relative velocities of surrounding vehicles. The driver behavior in segment 1 is highly dependent on the number of surrounding vehicles, distances and their relative velocities. There are other important parameters such as road curvature, visibility condition or behavior of the surrounding vehicles. We also found that time/distance constraint is also a critical factor to select the suitable behavior at segment 1. It occurs when we try to merge into highway traffic or exit from




(a) Human lane change data.




(b) Two segments model.

Fig. 1. Two segments lane change model.

the highway. By analyzing different cases of human lane change data, we extracted the following behaviors for the segment 1.

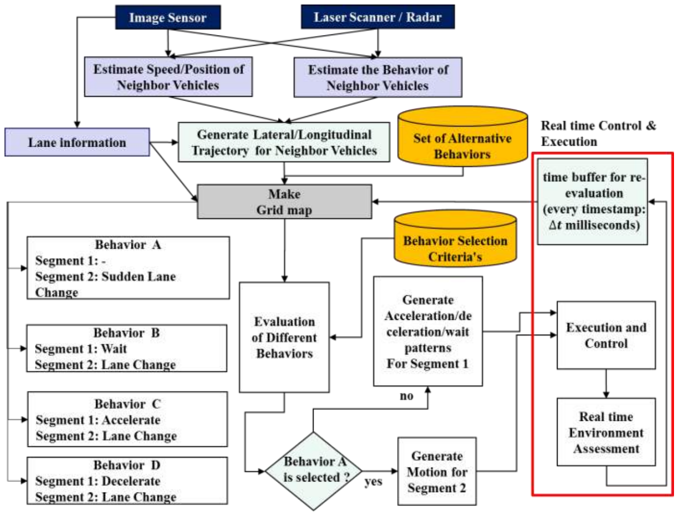



Fig. 2 Automatic lane change flowchart.

$$\mathrm{B} = \{do\ lane\ change(LC), wait, accelerate, decelerate, evasive\} \quad (1)$$

Although, it is difficult to develop a general behavior model but we can propose a standard model that guarantee the safety and smoothness of the lane change operation. For example, if there is enough space at the destination lane, we can turn the steering wheel and ***do the lane change (LC)***. If the relative speed of the approaching vehicles in the destination lane is relatively high, we may prefer to wait until find enough free space. In this case, we may even do ***deceleration*** to reduce the time or traveled distance. The deceleration behavior may be useful in the case of time/distance constraint when we have to change the lane to exit from the highway. In the other case, when the relative speed of the neighbor vehicles in the destination lane is relatively low, we may ***accelerate*** to pass the neighbor vehicles for doing the lane change. If we have a sudden change in the behavior of the surrounding vehicles during the lane change (sudden acceleration, deceleration or lane change), we may need ***evasive*** maneuver to avoid accident. In the other hand, the road curvature and speed limits and kinematic constraints of the vehicles such as maximum speed or acceleration have also impact on the driver behavior.

### *2.1 Lane Change Flowchart*

Automatic lane change is integration of sensing/perception, planning (behavior & motion) and control. The behavior/motion flowchart for doing the lane change is shown in Fig. 2. It starts with estimation of motion parameters/ position of neighbor vehicles to estimate their trajectories. Based on the driving lane information and the behavior/motion parameters of the neighbor vehicles, we are able to estimate a trajectory for a certain period [0~T]. By using the trajectory data points $(t, x(t), y(t))$, we estimate the occupancy grid map of current and future state of the surrounding environment. In the following, we briefly explain the main components of the lane change flowchart.

### *2.2 Situation Modelling*

We model the current lane change situation into a state occupancy grid as in the Fig. 3. This state grid is attached to the vehicle position.

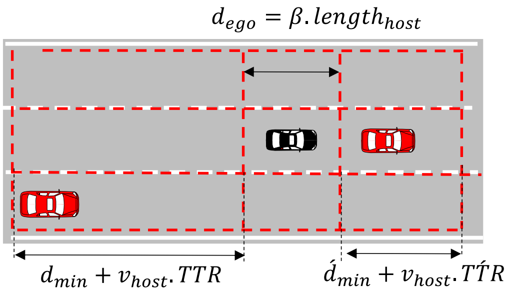



Fig. 3. Environment grid modelling.

The grid cell's width and orientation are equal to the lane width. The middle cell length $d_{ego}$ is equal to the ego vehicle length plus a safety distance at the front and back size. The gird's front cell size is calculated based on the current velocity and time to react.

$$d_{safe} = d_{min} + v_{host} * TTR \quad (2)$$

where $d_{min}$ is a human defined minimum safety distance; $v_{host}$ is the current ego vehicle's velocity, and $TTR$ is time to react in case of some emergency situation happening (e.g. the car in the front suddenly stops). The space needed is depent on the ego vehicle's speed and the surrounding vehicle's speed. A longer distance is needed when the vehicle is travelling at high speed. The scenario around the ego vehicle can now be modelled into a grid of 8 states and labelled/numbered as in Fig.4. Each cell in the grid has one state of either "empty" or "occupied".

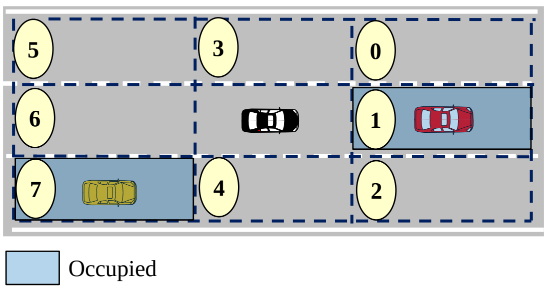
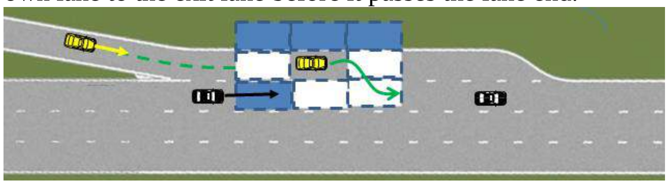



Fig. 4. Observation grid state.

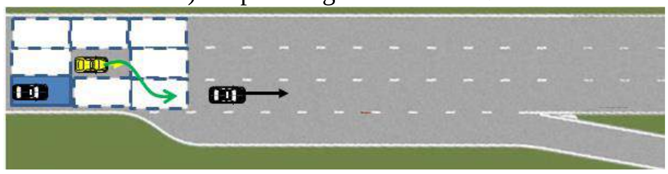
If cell (1) is "empty" then it means there is no obstacle inside the space that's required in front of ego vehicle. Similar meaning is applied for other cells. That means if cell (0),(1),(3), and (5) are "empty", the ego vehicle has sufficient space to perform the left side lane change. Besides, if the entire surrounding vehicles travel with a relatively equal speed then it is also possible to change to right side lane. Similarly, when the vehicle is travelling at the right-most lane, corresponding right side cells are set to be occupied.

By discretization the surrounding environment to a nine-cell grid, we are able to present different states to do the lane change. We have eight surrounding cells in the occupancy grid that can be free (cell value = 0) or occupied (cell value = 1) then we have totally $2^8$ =256 states. Since the vehicle only perform either the left side or right side lane changing maneuverer, we can temporarily ignore the other side's cell so that the number of state can be reduced to $2^5$ = 32 states.

For merge-in maneuver from a side road to main lane, according to traffic rules, a direct cut-in is considered dangerous or unsafe maneuver and Figure 5.a) illustrates a proper merge in maneuver. We apply the grid state model from the entrance of the ramp road. Figure 5.b) illustrates an exiting from main line situation, the vehicle needs to change own lane to the exit lane before it passes the lane end.



a) Proper merge in maneuver.



b)Lane change for exitting from main line traffic.

Fig. 5. Merge in and exit lane.

### *2.3 Behaviour Generation*

For every state, we consider different alternative behaviors as shown in Fig. 6. For the occupancy grid state in Fig. 6, different following behaviors are available to do the lane change;

- **Case A:** The host vehicle just waits until the right lane

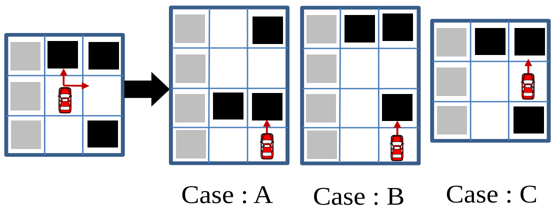



Fig. 6. Different available behavior and motion for lane change.

approaching vehicles passes it and the right lane becomes free to do right lane change.

- **Case B:** In this case, the host vehicle decelerates and enters to the right lane. It is preferable behavior when we have to do the lane change at limited time/distance (for example exit point in the highway).
- **Case C:** In this case, the host vehicle does the lane change as there is enough space and the relative velocities of the vehicle in the right lane is not high.

To have exact understanding of different behaviors, we categorized 32 ($2^5$) occupancy gird states (left or right lane change) to the following main four categories. We limit the behavior alternatives based on the categories to reduce the calculation time. Different categories for occupancy grid states are shown in Fig. 7, and we explain the characteristics of each categories and available alternative behaviors for each state. The categories and alternative behaviors are defined based on our experiments from analyzing the human driver data for different lane change scenarios.

- **Category A:** We have two alternative behaviors for occupancy grid states. We either wait or do the lane change based on the relative speed and distance to the neighbor vehicles.

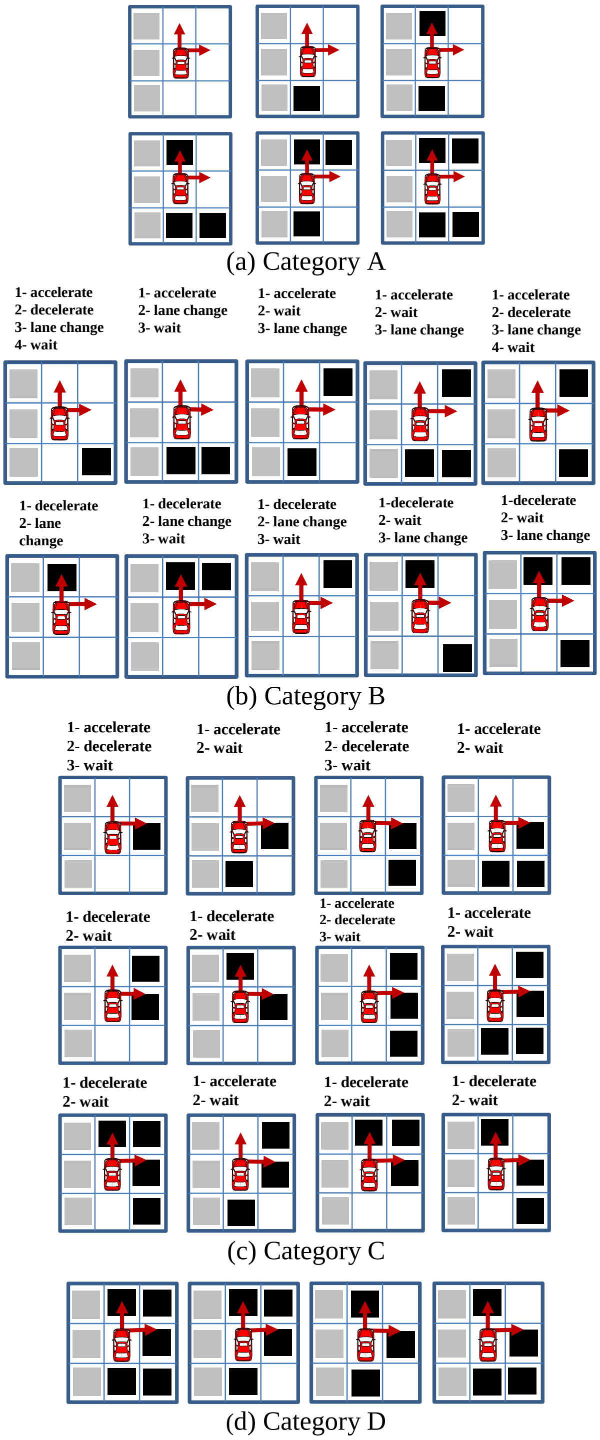



Fig. 7. All 32 states models for right lane change and available alternative behaviours for each of them.

- **Category B:** We have more alternative behaviors for states in this category. We may do the lane change but sometimes acceleration/deceleration or wait is preferable to do safer/smoother lane change. In the case of time/distance constraint, acceleration/deceleration may necessary to satisfy the lane change limitations.

- **Category C:** It is related to complicated state during lane change. In this category, the right cell of the host vehicle is occupied and suitable behavior should be selected to provide free space at the destination lane. We may accelerate, decelerate or wait for states in this category.

- **Category D:** We have to wait for doing the lane change and any other behavior may cause danger.

For situation that has more than one behavior option, we prefer the waiting and deceleration action since it provides the vehicle more time to perform lane change maneuver. We define an evaluation function which consists of three main parts including safety, smoothness (comfortable) and the operation time (travelled distance) to select the suitable behaviour for each state.

### *2.4 Velocity Planning (Behaviour Segment)*

According to the decided behavior, we calculate the corresponding desired vehicle's velocity profile. The acceleration/deceleration patterns are presented in the form of a function that considers ego vehicle position, velocity and the target leading/behind vehicle.

In Fig 8, we illustrate the vehicle acceleration behavior when a leading vehicle is present in the neighboring lane. In this scenario, our vehicle decides to accelerate and pass the leading vehicle. The acceleration is continued till sufficient safe distance is achieved, before performing the lane change maneuver.

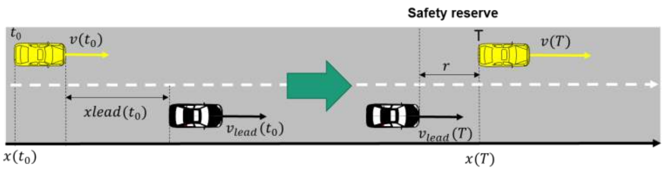



Fig. 8. Vehicle acceleration for passing.

The ego vehicle's acceleration is calculated based on (3):

$$\ddot{x} = 2(x_{lead}(t_0) - x(t_0) + T(v_{lead}(t_0) - v(t_0)) + r)/T^2 \tag{3}$$

where $x(t_0), v(t_0)$ are the vehicle position and velocity at time $t_0$; $x_{lead}(t_0)$, $v_{lead}(t_0)$ are leading vehicle position and velocity at time $t_0$; $T$ is the operation time horizon; $r$ is a safety reserving distance and calculated through leading vehicle velocity and time to react $TTR$

$$r = d_{min} + v_{lead}(T) * TTR \tag{4}$$

Similarly, for other decisions, we can calculate the vehicle desired position and corresponding velocity profile. This velocity profile will be used for trajectory planning.
To generate smooth and comfort acceleration/deceleration motion, we minimize the following cost function;

$$J = \int_0^T (\omega_{dist}[\Delta d(t)]^2 + \omega_{acc}[\ddot{x}(t)]^2)dt \tag{5}$$

This cost function is similar to the method presented in (Geiger et al., 2012) though the operation time $T$ is fixed. In our approach, the operation time $T$ is not fixed to have more degree of freedom for behavior in segment 1. The error in the safety distance ($\Delta d(t)$) is calculated by the following;

$$\Delta d(t) = x_{lead}(t) - r + t * \dot{x}_{lead}(t) - x(t) \quad (6)$$

We use quartic polynomial to generate acceleration/deceleration motion (D. Althoff, et al., 2012).

$$x(\mathrm{t}) = b_4 t^4 + b_3 t^3 + b_2 t^2 + b_1 t + b_0 \quad (7)$$

We estimate the coefficients $b_i (i = \overline{0,4})$ by considering vehicle constraints (maximum acceleration/deceleration and speed), desired velocity and operation time. We sample from valid range of operation time T and final velocity $\dot{x}(\mathrm{T})$ to generate alternative longitudinal trajectories while considering the boundary conditions including maximum and minimum acceleration $\ddot{x}_{max}, \ddot{x}_{min}$ .

*2. 5 Motion Segment*

To model a geometric path during a lane change, literature show often approaches using 5th degree polynomials [10, 11]. Polynomial function provides a geometric modelling of the vehicle trajectory that responds to the realistic demands of the maneuver. Quintic polynomials as following, used to generate alternative lateral trajectories

$$y(\mathrm{t}) = a_5 t^5 + a_4 t^4 + a_3 t^3 + a_2 t^2 + a_1 t + a_0 \quad (8)$$

The equation coefficients $a_i (i = \overline{0,4})$ are calculated considering dynamic constraints (boundary conditions for lateral acceleration) and values of the position, velocity and acceleration at initial and endpoint. We are able to get the initial velocity and acceleration of vehicle from the CAN and generate alternative lateral trajectories by changing operation time T. We sample T from valid range of operation time and end conditions to generate alternative lateral trajectories c considering the boundary conditions including $\ddot{y}_{max}, \ddot{y}_{min}$ and $\kappa(t) \leq \frac{\ddot{y}_{max}}{\dot{x}(t)^2}$ to avoid slip.

We optimize the lateral motion by minimizing the following cost function that includes lateral jerk, heading error and smoothness as shown in Fig. 9;

$$J = w_{jerk} \int_0^T \dddot{y}^2(t) + w_{heading}[\kappa(T) - \kappa_{road}]^2 + w_{smoothness} \int_0^T \frac{\dot{\kappa}(t)^2}{\sqrt{\dot{x}(t)^2 + \dot{y}(t)^2}} \quad (9)$$

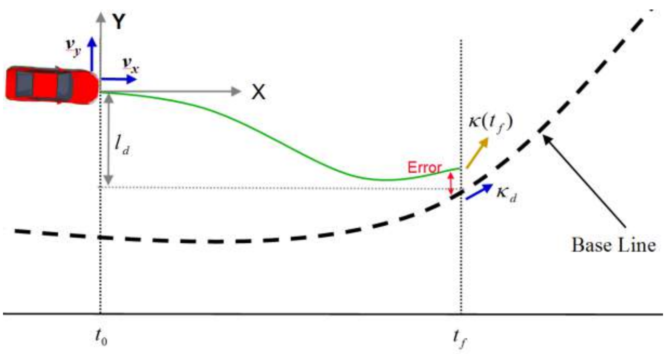



Fig. 9. Lateral trajectory optimization.

3. SIMULATION

To evaluate and test the proposed model, we developed a simulation platform on the PreScan. It includes different modules for sensing, behaviour/motion planning, trajectory estimation of neighbour vehicles and control. Figure 10 shows simulation results for the lane change scenario in the case of distance constraint for exiting the highway (host vehicle is red and it is going to do right lane change to exit the highway). Refer to the Fig. 7, current observation grid status belongs to Category C and the host vehicle can select between *acceleration*, *deceleration* and *wait* behaviour.

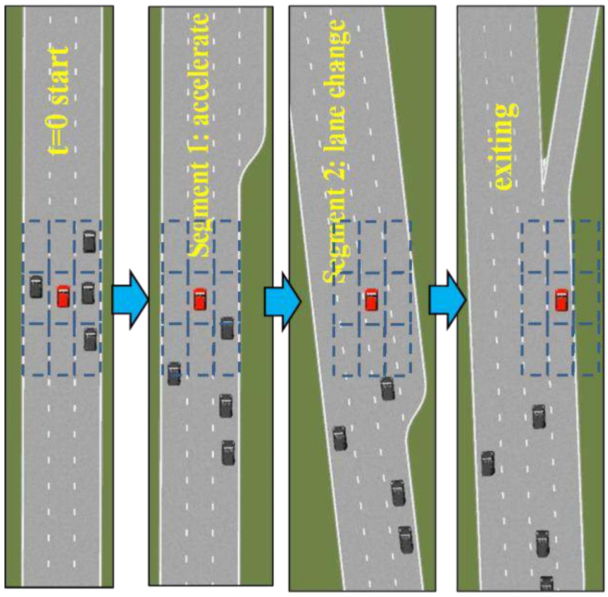
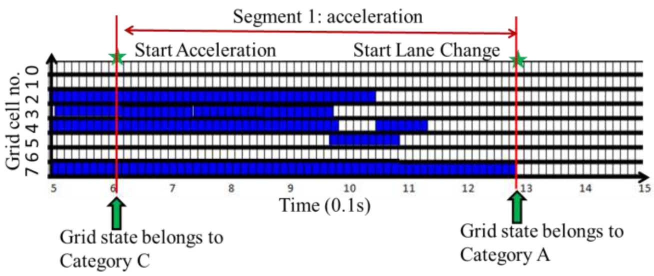
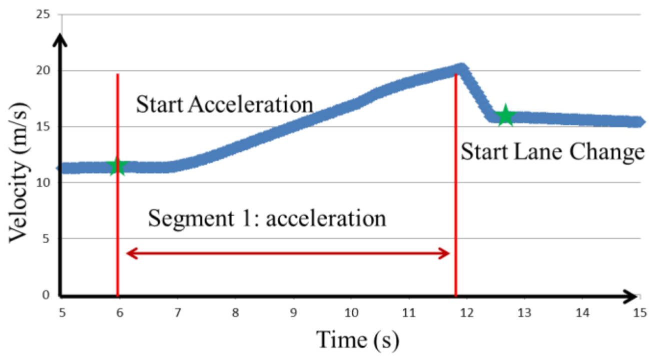



Fig. 10. Lane change simulation for exiting with acceleration behaviour.




a) Observation grid.




b) Velocity profile.

Fig. 11. Lateral position, velocity profile and observation grid state for acceleration behaviour.

Considering the time constraint for exiting and neighbour`s vehicle speed at the left lane, the *acceleration* or *deceleration* behaviours are preferable to meet the time constraint for doing the lane change. As the left lane neighbour's vehicles speed are lower than the host vehicle`s speed, the *acceleration* behaviour is selected for segment 1 and the velocity profile is generated as shown in Fig. 11(b). By doing acceleration, the host vehicle evaluates the state of the grid and when the state falls into Category A, it starts to do the left lane change. The state of observation gird is shown in Fig. 11 (a) and we are able to select suitable behaviour based on the grid state.

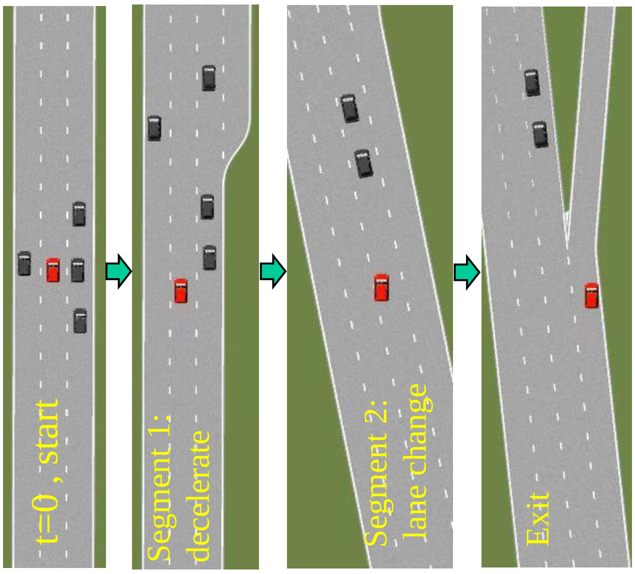
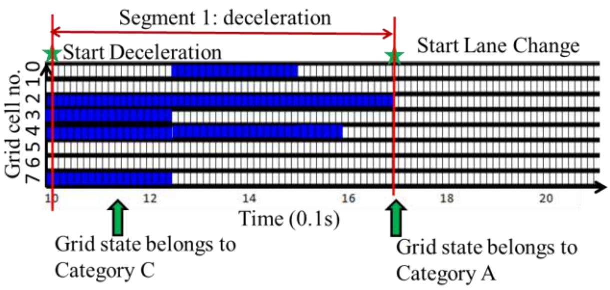
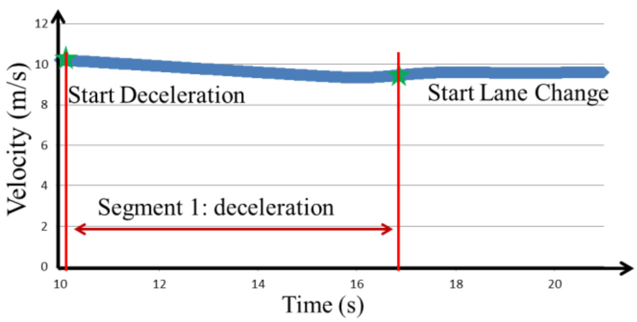



Fig. 12. Lane change simulation for exiting with deceleration behaviour.




a) Observation grid.




b) Velocity profile.

Fig. 13. Velocity profile and observation grid state for deceleration behaviour.

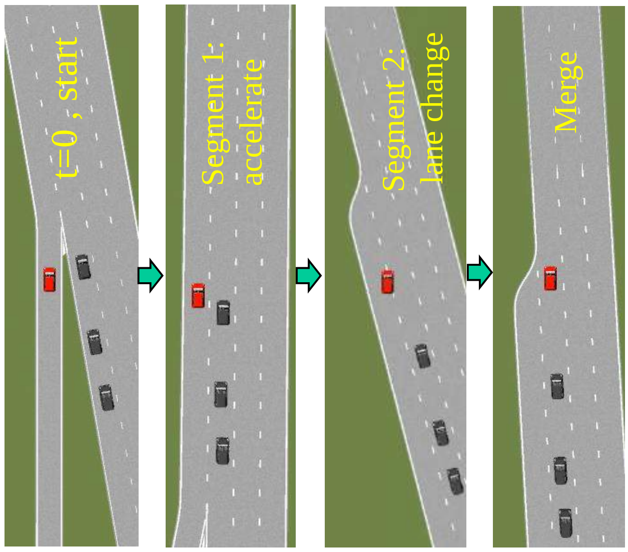
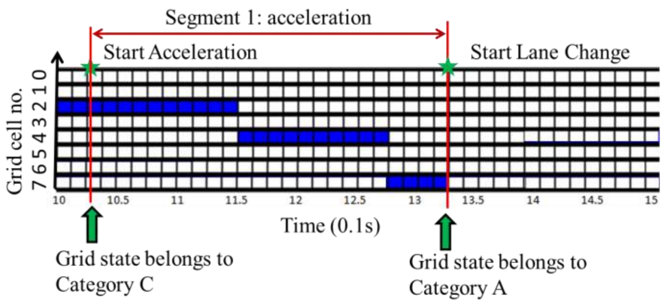
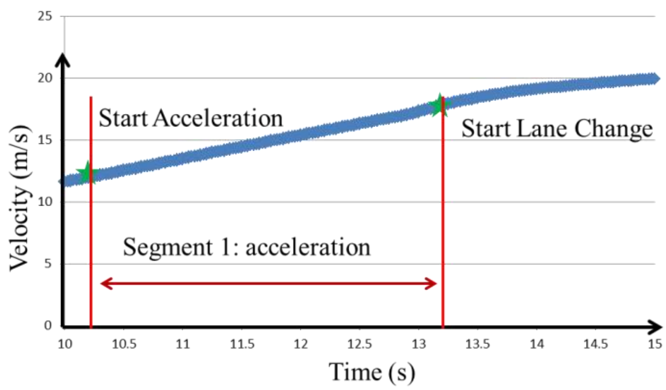



Fig. 14. Lane change simulation for merge in with acceleration behaviour.




a) Observation grid.




b) Velocity profile.

Fig. 15. Velocity profile and observation grid state for acceleration behaviour.

In these experiments, the host vehicle is travelling at speed of 12 m/s. The exit lane distance is 150m. The grid cell's width is equal to lane's width = 3.5m. The reaction time (TTR) is 1 second. Notice that, in this stage, we do not consider the interaction between drivers. Figure 12 also illustrates a lane change process for exiting, however, this time, the deceleration behaviour was chosen. In this case, left lane neighbour` vehicles speed are higher than the host vehicle's speed and the velocity profile is generated as shown in Fig. 13(a). As shown in Fig. 13 (b) the host vehicle try to change the state of the grid and when the state falls into Category A, it starts to do the left lane change. Figure 14, 16 show merging simulations to the highway. Same as exiting, the host vehicle selects the suitable behaviour based on in current state of observation gird and do the lane change when the grid state falls into category A. The suitable behaviour from acceleration and deceleration is selected based on the neighbour' vehicles speed and distances. We extracted the relative speed ranges and distances by doing lane change experiments at highway and recording the human behaviour at different scenarios. As shown in Fig.11 when the vehicle applies acceleration behaviour, although it take shorter time to reach suitable lane change state, the vehicle needs to deceleration since it comes close to the exiting-lane's entrance. If the ego vehicle applies deceleration behaviour as shown in Fig. 13, it took longer time to find suitable state for lane change. Similar situation happens for enter-lane cases as in Fig.15 and Fig.17.

## 4. CONCLUSIONS

In this paper, a behaviour/motion model for automatic lane change at highway has been proposed. The proposed model is mainly inspired by human driver lane change and behaviour data and can handle difficult lane change scenarios. The observation grid state was presented to model the environment/situation. The occupancy grid states are categorized and alternative behaviours are defined for each corresponding category. In the future, we are going to do lane change experiments by human drivers to extract the reference samples and learn the behaviour selection function. Our current behaviour model does not consider the interaction between the vehicles so that in future work, our model will involve it.

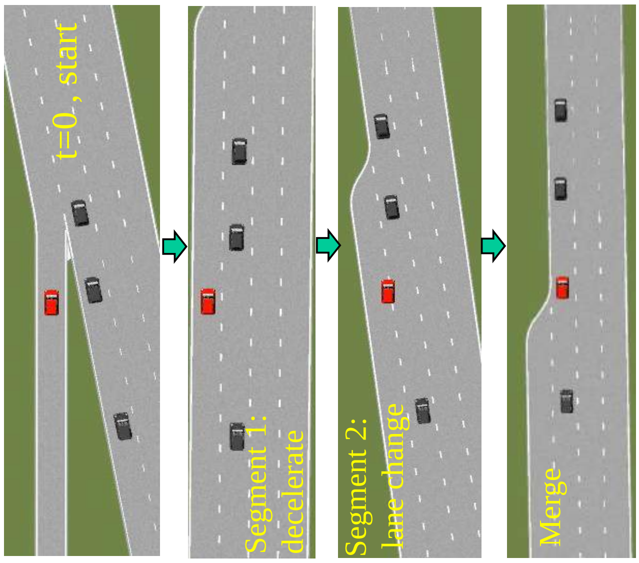
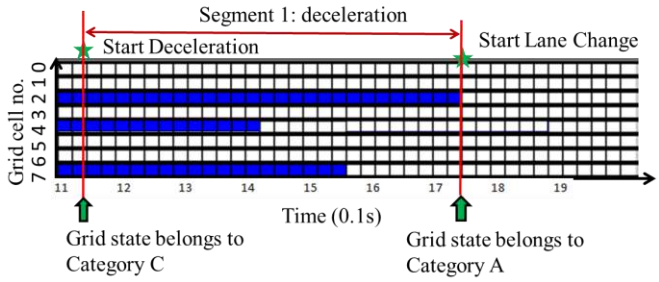
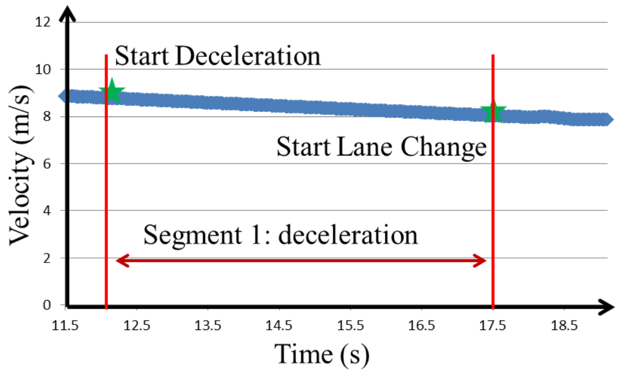



Fig. 16. Lane change simulation for merge in with deceleration behaviour.




a) Observation grid.




b) Velocity profile.

Fig. 17. Velocity profile and observation grid state for deceleration behaviour.

## REFERENCES

Althoff, D., Buss, M., Lawitzky, A., Werling, M., and Wollherr, D. (2012). On-line Trajectory Generation for Safe and Optimal Vehicle Motion Planning. *AMS 2012*, pp. 99-107.

Ardelt, M., Coester, C. and Kaempchen N. 2012. Highly automated driving on freeways in real traffic using a probabilistic framework. in *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 4, pp. 1576-1585.

Brechtel, S., Gindele, T. and Dillmann, R. (2011). Probabilistic MDP-behavior planning for cars. *14th International IEEE Conference on Intelligent Transportation Systems*, pp.1537-1542.

Dolan, W. and Litkouhi, B. (2010). A prediction- and cost function-based algorithm for robust autonomous freeway driving. *2010 IEEE Intelligent Vehicles Symposium (IV)*, pp. 512–517.

Fletcher, L. et al. (2009). *The DARPA Urban Challenge*, volume 56 of Springer Tracts in Advanced Robotics, pp. 509–548. Springer Berlin Heidelberg.

Geiger, A A., Lauer, M., Moosmann, F., Ranf, B., et al. (2012). Team AnnieWAY's Entry to the 2011 Grand Cooperative Driving Challenge. *IEEE Transactions on Intelligent Transportation Systems*, vol 13, no 3, pp. 1008 – 1017.

Jula, H., Kosmatopoulos, E. and Ioannou, P. 2000. Collision avoidance analysis for lane changing and merging. *IEEE Transactions on Vehicle Technology*, vol. 49, pp.2295 - 2308.

Kasper, D., Weidl, G., Dang T, et al. (2014). Object-Oriented Bayesian Networks for Detection of Lane Change Maneuvers. *Intelligent Transportation Systems Magazine*, Vol. 4, No. 1, pp.19-31.

Naranjo, J. E, Gonzalez, C., Garcia, R. and de Pedro, T. (2008). Lane-Change Fuzzy Control in Autonomous Vehicles for the Overtaking Maneuver. *IEEE Transactions on Intelligent Transportation Systems*, vol. 9, no. 3, pp. 438-450.

Schubert, R., Schulze, K. and Wanielik, G. (2010). Situation Assessment for Automatic Lane-Change Maneuvers. *IEEE Transactions on Intelligent Transportation Systems*, vol. 11, no. 3, pp. 607-616.

Simon, U. and Markus, M. (2013). Probabilistic Online POMDP Decision Making for Lane Changes in Fully Automated Driving. *Proceedings of IEEE Conference on Intelligent Transportation Systems*, pp.2063-2070.

Tehrani, H., Muto, K., Yoneda, K. and Mita, S. (2014). Evaluating human & computer for expressway lane changing. *IEEE Intelligent Vehicles Symposium Proceedings*, pp. 382 – 387.

Volvo Trucks, European Accident Research and Safety Report.[Online]http://www.volvotrucks.com/SiteCollectionDocuments/VTC/Corporate/Values/ART%20Report%202013_150dpi.pdf, 2013.

Ziegler, J., Bender, P., Dang, T. and Stiller, C. (2014). Motion planning for Bertha - a local, continuous method. *Proceedings of Intelligent Vehicles Symposium*, Dearborn, Michigan, USA, pp. 450-457.