Autonomous Overtaking Maneuver Design based on Follow the Gap Method

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Abstract: This paper proposes a solution for one of the most important components of autonomous driving: "overtaking maneuver". Follow the Gap method (FGM) is oneof the most popular obstacle avoidance algorithms and directly obtains steering angle from position of the obstacles around. This paper is the first study using FGM to solve the overtaking problem. Different from previous studies where a trajectory is planned and then a controller is designed to track it; we use FGM for motion planning and control together. This paper focuses on overtaking maneuver in a challenging environment like highway traffic where the safety and fast response are the key factors. After we adapt the FGM to overtaking problem, we compare it with an existing overtaking method X-sin functions from literature. Since X-sin functions method requires a path tracker (controller), Stanley method is combined with X-sin functions. At the end of this work, we show several advantages of FGM comparing to the X-sin functions based overtaking approach.

1 INTRODUCTION

With the rapid development of technology in recent years, the automotive industry is moving closer to full autonomous vehicles. The most critical benefit of autonomous driving is human safety. Every year approximately 1.35 million people die because of traffic accidents according to "Global Status Report on Road Safety" (Toroyan, 2018). In addition, 25-78% of accidents happened as a result of driver inattention (Klauer et al., 2010) and 10% of all crashes happened during the lane change (G. M. Fitch and Dingus, 2009). In order to avoid crashes, one of the most important thing to do is providing fast response.

Global path planning algorithms requires high computational time for their operations. For example A*, which is one of the most popular graph search algorithm, finds a path from point A to B for static maps (Likhachev and Ferguson, 2009). On the other hand, it is not very convenient to find a new path using A* if the map changes very often as in dynamic environments. D* is introduced as improved A* which is more adaptable to moving obstacles but still not as fast as obstacle avoidance methods (Stentz, 1994). Nonholonomic constrains of vehicle are considered in "Rapidly Exploring Random Tree (RRT)" method which is a probabilistic approach and provides a smooth driving (Lavalle, 1998). The main drawback of these kind of methods is the required computational time. Moreover, afters suitable trajectory is generated, the trajectory must be followed by a path tracker algorithm.

The aim of a path tracker algorithm is to calculate the required control inputs reach from one waypoint to another. Stanley (Snider, 2009) method and Pure Pursuit (Coulter, 1992) are two popular tracking algorithms.The comparison of these two approaches is shown (Cibooglu et al., 2017) which proposes a hybrid method at the end. According to the analysis, Pure Pursuit does not provide a good performance in cutting roads and Stanley method overshoots at sharp corners. Another result from analysis is Stanley method has more advantages than Pure Pursuit at high speeds.

For the solution of overtaking problem, Mixed Observable Markov Decision Process (MOMDP) based solution is provided in (Sezer, 2018). However, this solution is not suitable for real-time applications due to its computational complexity. Moreover discrete state space representation restricts the operation of the method. Another overtaking approach X-sin is proposed in (Zhang et al., 2014) which provides ap-

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propriate path using special trigonometric functions. It requires three main parameters for its operation and calculation of the path is relatively easy. On the other hand it still needs a controller algorithm in order to track the desired path.

Obstacle avoidance algorithms are mostly used for dynamic environments in order to avoid any obstacle in a short time. For example bug algorithms (Zohaib et al., 2013) are based on following the borders of the obstacles but not useful to implement for highway driving and vehicle dynamics. Another obstacle avoidance algorithm is Artificial Potential Field Method (Zhu et al., 2006) and (Bounini et al., 2017) which results smooth steering angles. However, the tuning parameters can affect the steering angle a lot and it should be adapted for every situation in highway driving while very different scenarios are possible. Local minimum problem is another critical disadvantage of this approach.

Follow the Gap method (Sezer and Gokasan, 2012) is a geometric obstacle avoidance algorithm for autonomous driving. FGM selects the maximum gap angle in the field of view, it combines the the goal angle and gap angle considering minimum distance to obstacle. It also considers the nonholonomic constraints of the vehicle, does not have local minimum problem and is easy to tune with only one tuning parameter. Improved Follow the Gap (FGM-I) (Demir and Sezer, 2017) is an extended version of FGM which solves two drawbacks of original FGM. FGM-I eliminates chattering effect coming from unnecessary gap change and chooses goal oriented gaps in order to find a shorter path.

This paper examines the overtaking in highway conditions where the speed values are relatively high. Dynamic single track vehicle model is used in order to obtain more realistic results comparing to pure kinematic models (Rajamani, 2011).

In this paper, FGM is implemented as motion planning and controlling algorithm and compared with X-sin functions planner and Stanley controller.

Vehicle model, FGM and X-sin planner with Stanley controller (XwS) are explained in section 2, simulation environment and highway scenarios are explained in section 3 , and simulation results through the implementation are shown in section 4. Conclusion of the paper is examined in section 5. Future Work is provided in section 6.

2 TECHNICAL APPROACH

The general approach in autonomous driving is designing a motion planner and a controller as separated components. As it is shown in Figure 1, X-sin function as a motion planner generates a collision free path in accordance with environment (Zhang et al., 2014). The path is controlled by the Stanley controller which obtains the steering angle to be given to vehicle model (Snider, 2009). From now on we call XwS for the combination of X-sin functions motion planner and Stanley controller. The principle of operation of X-sin functions and Stanley method are explained in Section 2.3.

The proposed approach is to combine motion planner and controller using FGM for overtaking maneuver as it is stated in Figure 2. Follow the Gap method combines motion planner and controller by itself so that quick reaction in dynamic environment is available while considering safety and comfort. The principle of operation of FGM is explained in Section 2.2.

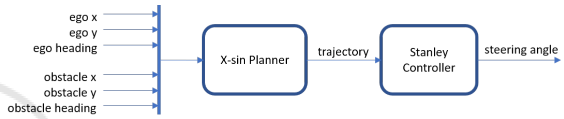

Figure 1: Concept of Motion Planing and Control using.

Figure 2: Concept of New Approach based on FGM.

2.1 Vehicle Model

In order to make realistic simulations, single track dynamic vehicle model (Rajamani, 2011) is used instead of a kinematic bicycle model which neglects tire forces. Even though the kinematic model is applicable at lower speeds, dynamic model is required for highway scenarios at high speeds. Since this work concentrates on overtaking maneuver, longitudinal speed is considered as constant. Dynamic bicycle model is represented as it is shown in Figure 3. X, Y represent the global coordinates, x, y represent the local coordinate of vehicle where CG is the vehicle's center of gravity. L_f is the distance from center of gravity to front wheel and L_r is the distance from CG to rear wheel. δ and ψ are the steering angle and yaw angle of the vehicle, respectively. Finally, F_{yf} and F_{yr} represent the lateral forces.

(1) and (2) are standard equations for lateral dynamics. x, y positions of ego vehicle and yaw angle are obtained by the (2), (3) and (4).

$$m\dot{v} = F_{yf}cos(\delta) + F_{yr} + mv_x\dot{\psi} \quad (1)$$

$$I_z\ddot{\psi} = L_fF_{yf}cos(\delta) - L_rF_{yr} \quad (2)$$

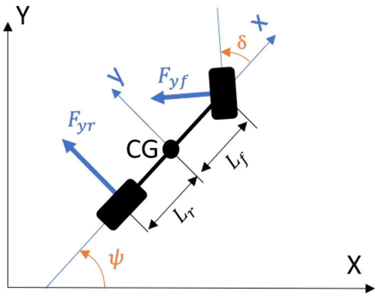

Figure 3: Single Track Lateral Dynamics.

$$\dot{x} = v_x cos\psi - v_y sin\psi \tag{3}$$

$$\dot{y} = v_x sin\psi + v_y cos\psi \tag{4}$$

2.2 Follow the Gap Method

FGM basically monitors the maximum gap between the closest obstacles in field of view and generates a steering angle which avoids the obstacles considering the goal point (Sezer and Gokasan, 2012). FGM generates desired heading angle which can be used as steering angle directly. Figure 4 shows the angles regarding to FGM; orange X is the starting point, red X is the target point, black dots represent obstacles, red dashed line represents the connection between starting point and goal point, black dashed line represents the connection between starting point and gap center of selected obstacles in the field of view, d_n is the distance from ego vehicle to the n^{th} obstacle, ϕ_n is the angle of the n^{th} gap, ϕ_{gap} is the angle of the selected gap which is developed by the FGM, ϕ_{goal} is the angle from ego the goal point. (5) calculates ϕ_{gap} in terms of measurable variables, and (6) provides ϕ_{final} which is the final angle for the vehicle. α is a tuning parameter and selected as 0.5 according to experimental results. The higher α means the more importance on ϕ_{gap} so that ϕ_{final} is closer to the ϕ_{gap}. The lower α means the more importance on ϕ_{goal} therefore phi_{final} is weighted more on ϕ_{goal}. d_{min} is the closest distance from the nearest obstacle which weights ϕ_{goal} and ϕ_{gap} automatically. According to (6), when the ego vehicle approaches to an obstacle, ϕ_{gap} is weighted more than ϕ_{goal} and vice versa.

$$\phi_{gap_n} = cos^{-1}\left(\frac{d_n + d_{n+1}cos(\phi_n + \phi_{n+1})}{\sqrt{d_n^2 + d_{n+1}^2 + 2d_n d_{n+1} cos(\phi_n + \phi_{n+1})}}\right) - \phi_n \tag{5}$$

$$\phi_{final} = \frac{\frac{\alpha}{d_{min}}\phi_{gap} + \phi_{goal}}{\frac{\alpha}{d_{min}} + 1} \tag{6}$$

ϕ_{final} is the desired heading angle but can be directly used as steering angle as it is implemented in this paper. For different applications, an additional controller can be designed to calculate the steering angle in order to get the desired heading angle.

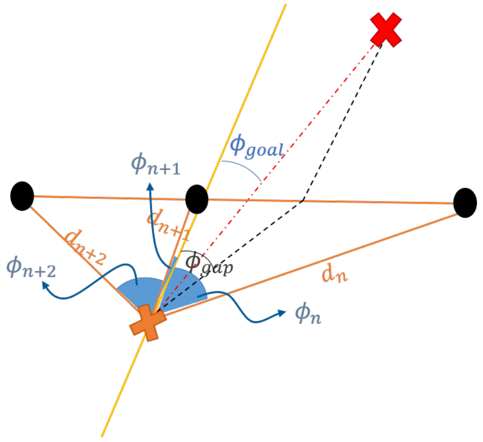

Figure 4: Follow the Gap Angle Representation.

2.2.1 Adaptation of FGM to Overtaking Maneuver

In order to adapt FGM for overtaking maneuver, we specify a single goal point that is located in front of the actor vehicle. This goal point moves with the actor vehicle. Actor vehicle is also an obstacle for ego vehicle. The borders of the road are also other obstacles for ego vehicle. If FGM is used as an obstacle avoidance algorithm to reach the goal point which is defined in front of actor vehicle, the final trajectory becomes an overtaking maneuver.

The flowchart of overtaking algorithm using FGM is shown in Figure 5. First, time to collision T_{tc} value is calculated as shown in (7). The algorithm checks whether that T_{tc} value is lower than 2 seconds. This experimental value is selected according to (Kristofer D. Kusano, 2011). This first part of the approach is preparation for lane change as shown in Figure 6. In this figure, red X is defined as the goal point and blue dots are obstacles. If T_{tc} value is lower than 2 seconds, the ego vehicle starts lane changing using FGM.

$$T_{tc} = \frac{d_{eto}}{V_{net}} \tag{7}$$

d_{eto} : Distance between ego vehicle to obstacle [m], T_{tc} : Time to Collision [s], V_{net} : Velocity difference between ego and actor vehicles [m/s]

Secondly, FGM finds the gap goes forward to the gap until it reaches the rear left corner of the front actor vehicle which is shown in Figure 7. This is the passing phase of overtaking maneuver. Look ahead range (LAR) distance is added in order to avoid the quick and dangerous merging so that ego vehicle keeps its lane until it reaches the location that is defined by LAR.

Finally, ego vehicle starts to steer to get back to the initial lane where LAR away from actor vehicle. This last phase of overtaking is called "merging" as shown in Figure 8.

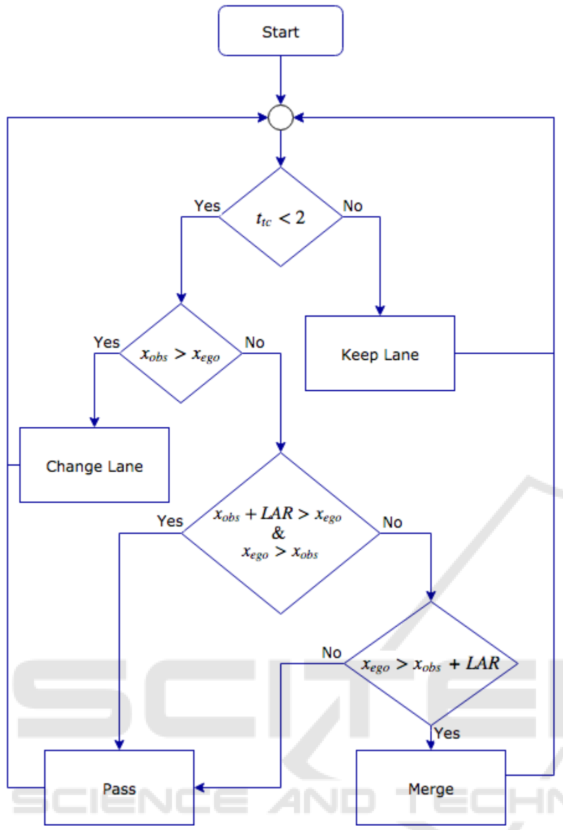

Figure 5: Algorithm of Overtaking.

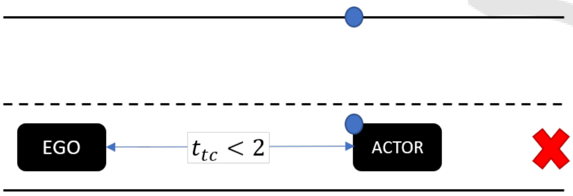

Figure 6: Lane Change using FGM.

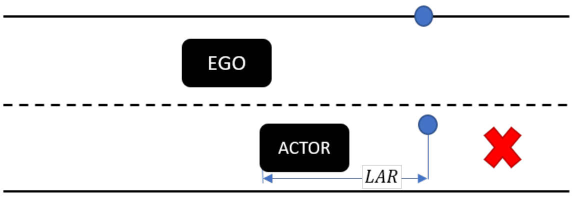

Figure 7: Passing the actor vehicle using FGM.

In section 4, three different speed scenarios are presented and overtaking performances of FGM are declared.

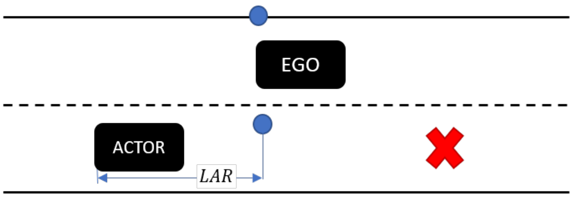

Figure 8: Merging using FGM.

2.3 X-sin Function as a Motion Planner and Stanley Method as a Motion Controller

2.3.1 X-sin Function as a Motion Planner

X-sin function was developed as a solution for overtaking maneuver using standard mathematical functions in (Zhang et al., 2014). X-sin is a partial function which calculates the lateral and longitudinal position of the ego vehicle as illustrated in Figure 9. Overtaking decision is made in the same way as in previous FGM approach by using (7). Goal position is selected in the end of the merging distance which dynamically moves with actor vehicle.

Figure 9 shows the parameters and trajectory of a typical X-sin function. L_d is the distance of lane changing, O_d is defined as distance of passing which is chosen as the length of the ego vehicle and M_d is the distance of merging which is selected as same as L_d.

Eq. (8) provides the mathematical function of X-sin where x is the current position and y_d is the lane change distance in y axis.

$$y(x) = \begin{cases} y_d\left[\frac{2\pi}{L_d}x - sin\left(\frac{2\pi}{L_d}x\right)\right] & x \in [0, L_d] \\ y_d & x \in [L_d, L_d + O_d] \\ y_d - y_d\left[\frac{2\pi}{L_d}x - sin\left(\frac{2\pi}{L_d}x\right)\right] & x \in [L_d + O_d, L_d + O_d + M_d] \end{cases} \tag{8}$$

The L_d parameter in X-sin is critical for a comfortable overtaking maneuver. Original paper (Zhang et al., 2014) proposes an equation which calculates a good L_d as shown in (9). The maximum allowed acceleration limit a_{max} is declared in (Zhang et al., 2014) as between $1-4m/s^2$ and v_x is the longitudinal speed of the ego vehicle. In this paper, a_{max} is selected $3m/s^2$ and L_d is calculated according to the vehicle speed v_x in section 4. M_d is selected same as L_d.

$$L_d = v_x\sqrt{\frac{2\pi y_d}{a_{max}}} \tag{9}$$

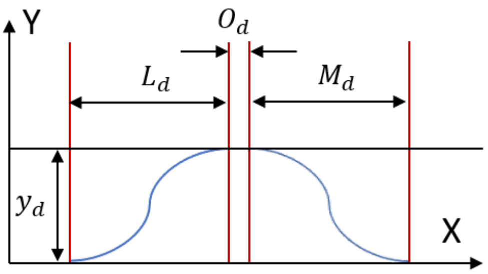

Figure 9: X-sin function representation.

2.3.2 Stanley Method as a Motion Controller

Stanley Method is commonly implemented as a motion controller for autonomous vehicles (Snider, 2009). In this paper, Stanley method is developed as a motion controller to track the trajectory which is generated by X-sin function. Stanley controller calculates the steering angle using yaw error and cross track error which are represented in (10). Figure 10 illustrates the Stanley method and shows the steering angle, heading angle, lateral error and longitudinal speed variables in detail.

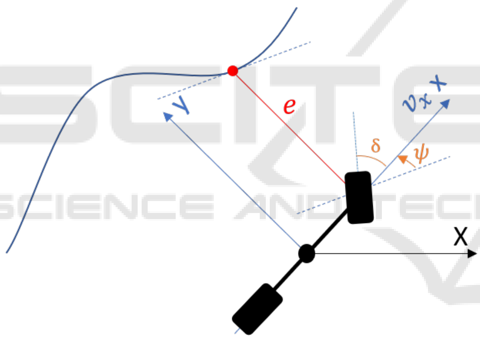

Figure 10: Stanley Controller Representation.

$$\delta(t) = \psi(t) + tan^{-1}\left(\frac{ke(t)}{v_x(t)}\right) \quad (10)$$

Cross track error $e(t)$ is the lateral error which means the closest distance between the ego vehicle and the path. Yaw error ψ is the difference between the heading of closest path point and ego vehicle heading, v_x is longitudinal speed. k is the tuning parameter which is selected as 10 using trial and error technique in order to get the best performance.

3 SIMULATION ENVIRONMENT

Matlab/Simulink environment is used to generate vehicle models, to implement algorithms, to create simulation scenarios, and to compare both of the methods. The scenarios are selected considering highway traffic where the speed is between 10 - 35 m/s (KGM, 2018) with 3.5m lane width as it is defined in standards (EuroTest, 2007).

During simulations, initial positions, initial heading, distance to goal point, environment and limitations are in same manner for both of the methods for a fair comparison. Goal point is selected as the end of merging which is represented by M_d away from the actor vehicle. Goal point distance for FGM and XwS are selected same in the simulations which is calculated in (9).

4 RESULTS

In this paper, FGM and XwS are compared according to different speeds. This comparison is made using the safety metric, the comfort metric and the total traveled distance. The related metrics are calculated using the general norm equation which is shown in (11). We select p as 2, which means second norm of the signals are calculated. Similar metrics can be seen in (Sezer and Gokasan, 2012) and (Demir and Sezer, 2017).

$$||f||_p = \left(\int |f(t)|^p dt\right)^{1/p} \quad (11)$$

The $f(t)$ function for safety metric is defined as the distance between the ego and the actor vehicle. It means that if the distance between ego vehicle and actor vehicle is generally high, the safety metric results with higher values in another words this is a safer overtaking. The $f(t)$ function for comfort metric is defined as the yaw rate of the ego vehicle. The increase in this metric means that the change ego vehicle's yaw angle is high which is an uncomfortable situation for the passenger. Total path is additionally calculated for comparison.

Figure 11 and Figure 12 illustrates the results of overtaking for FGM and XwS. The time samples are added to represent the locations of ego vehicle and actor vehicle for each specific time sample.

Table 1 contains a detailed comparison of FGM and XwS by comfort metric, safety metric and total traveled path. For both FGM and XwS, the initial positions are same, goal positions are calculated by same method and both approaches are compared according to the identical speeds. Table 1 shows that, at the same speeds, both comfort metric and safety metric values of FGM are higher than XwS. The result of more comfortable and safer overtaking maneuver is longer paths as shown in Table 1. For example in Figure 11.a and Figure 12.a, it is clearly seen that, the total path of FGM is greater than the total path of

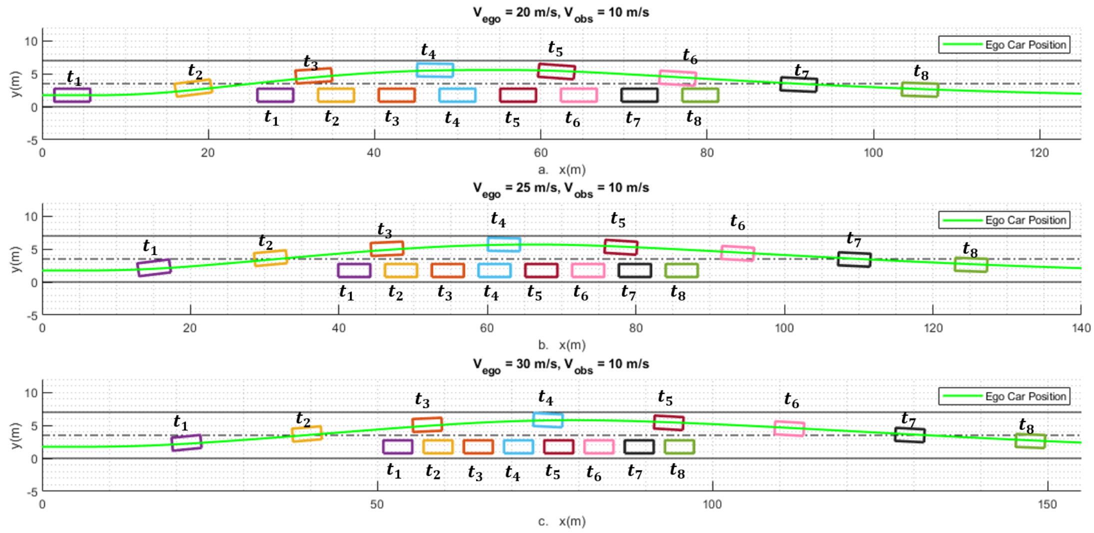

Figure 11: a. Overtaking by FGM at $V_{ego} = 20m/s$, b. Overtaking by FGM at $V_{ego} = 25m/s$, c. Overtaking by FGM at $V_{ego} = 30m/s$.

XwS when $V_{ego} = 20m/s$. The longer path of FGM occurs due to the passing part of overtaking maneuver. During the passing phase, when the ego vehicle is getting closer to the actor vehicle, d_{min} value decreases and ego vehicle intends to avoid from actor vehicle as calculated in (6).

Safer and more comfortable driving of FGM makes the increase of the total path less important. In Figure 12.c, the speed of ego vehicle is $30m/s$ and it is clearly seen that, Stanley method causes overshoot in control. This may cause more overshoots when the speed of ego vehicle is higher.

Table 1: FGM and Comparison Table.

Speed / Metrics		Comfort metric	Safety metric	Total Path [m]
20 m/s	FGM	216.45	21.21	146.84
	XwS	333.24	19.37	135.54
25 m/s	FGM	282.34	30.65	161.30
	XwS	484.05	25.50	153.77
30 m/s	FGM	371.90	40.16	184.27
	XwS	648.70	31.60	174.88

1000 Monte Carlo simulations are implemented to test FGM and in same environment to calculate the average improvement rate of FGM. The speed of the ego vehicle is assigned randomly between 10 - 20 m/s and the speed of actor vehicle is assigned randomly between 8 - 12 m/s. Each Monte Carlo simulation is performed by giving the same random speeds to the ego vehicle and the actor vehicle for FGM and XwS. According to the speeds of ego and actor vehicles, D_{eto}, L_d, M_d and the goal position are calculated. Average results of 1000 simulations are shown in Table 2.

According to the results the average comfort metric of FGM is 41% better and the average safety metric of FGM is 13% better than XwS results. On the other hand, the average total path of 1000 Monte Carlo simulations of FGM is 2.41% longer which is the result of safer paths. Overall, FGM is significantly safer and more comfortable than XwS and results with a little bit longer paths.

Table 2: Results of 1000 Monte Carlo Simulations.

Method / Metrics	Comfort metric	Safety metric	Total path [m]
FGM	290.15	31.21	164.02
XwS	493.96	27.01	160.15
Improvement Rate	41%	13%	-2.41%

5 CONCLUSION

In this paper, FGM is adapted for overtaking maneuver design and control. After this design, FGM is compared with XwS in highway overtaking scenarios. Dynamic single track vehicle model is used for simulations. One of the main differences between two approaches is; in XwS we need two separated solutions for planing and control while FGM is enough for both operations. Monte Carlo results show that FGM based overtaking solution is 13% safer and 41% more comfortable than XwS while the total traveled path is 2.41% longer. These results show that FGM is very suitable to solve the overtaking maneuver.

6 FUTURE WORK

Although FGM is an obstacle avoidance method, it is observed that it gives better results than XwS at high-

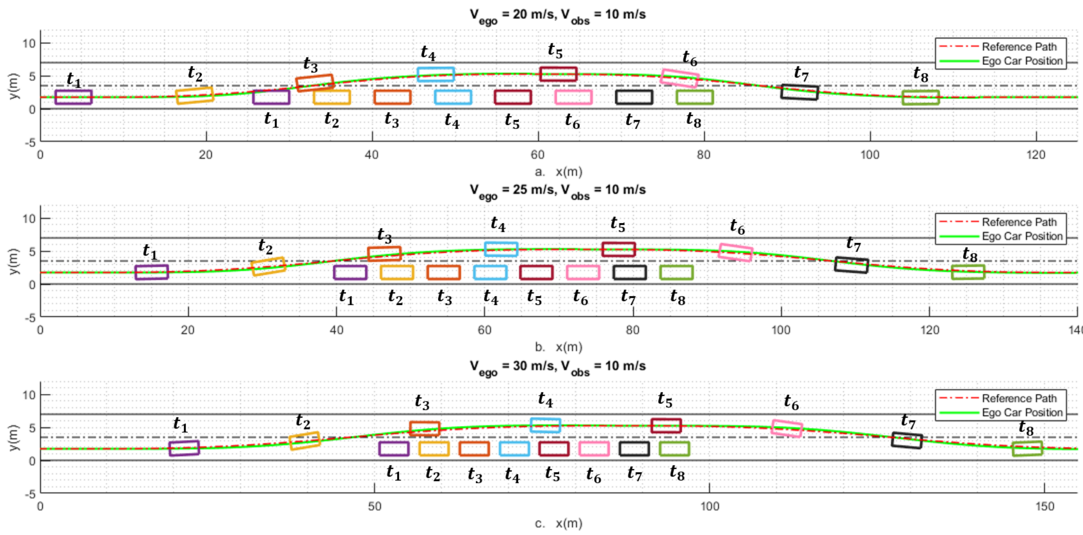

Figure 12: a. Overtaking by XwS at $V_{ego} = 20m/s$, b. Overtaking by XwS at $V_{ego} = 25m/s$, c. Overtaking by XwS at $V_{ego} = 30m/s$.

way conditions. The optimization of decision parameters for overtaking maneuver such as critical time to collision value or LAR distance can be thought as a future study. FGM would be very suitable for dynamic environments like urban because of its stability against moving obstacles. FGM is also easily adaptable for intersections, roundabouts or different types of junctions.

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