Amirkabir Journal of Mechanical Engineering

Amirkabir J. Mech. Eng., 54(8) (2022) 353-356
DOI: 10.22060/mej.2022.20809.7321

Head-on Collision Avoidance Path Planning with Model Predictive Control

M. Abdollahi Nia, A. Ghaffari*, S. Azadi

Department of Mechanical Engineering, K. N.Toosi University of Technology, Tehran, Iran

ABSTRACT: Due to the high fatalities of head-on accidents, the design of intelligent systems to prevent such severe collisions is essential. In this study, path planning for head-on collision avoidance with a deviated vehicle from the opposite lane has been investigated. The main approach is based on a model predictive controller with 2 seconds of prediction horizon and a linearized prediction model with low errors near the operational conditions. A conservative method is used for lateral motion prediction of the deviated vehicle and based on that, the collision avoidance constraints of the model predictive planner are simply modeled by a new approach. Moreover, a novel method to choose the proper swerve direction of evasive maneuver is proposed. This method is based on keeping the ego vehicle away from dangerous directions and has different criteria for far and close encounters. The final algorithm is capable to control the steering of the prediction model with a constrained lateral acceleration and calculates safe and maneuverable paths for the aforementioned scenario. Four simulations are conducted to validate the algorithm in far and close encountering, and critical conditions of choosing swerve direction. Results show the robustness of the path planner, even to sudden deviations at close distances and with high lateral accelerations.

Review History:

Received: Nov. 26, 2021
Revised: Feb. 25, 2022
Accepted: Jun. 27, 2022
Available Online: Jul. 13, 2022

Keywords:

Head-on collision avoidance
Path planning
Model predictive control
Constrained optimization

1- Introduction

Over the last decade, the development of perception systems, data fusion, and electromechanical actuators in the automotive industry, has paved the way for emerging of intelligent collision avoidance systems for critical situations. One of these situations is facing a deviated vehicle on a two-way road which can cause a severe head-on collision (Fig. 1). Almost 10 percent of global road fatalities are due to such accidents

The key aspect of collision avoidance systems focuses on planning real-time, safe, and maneuverable paths. Among different approaches of path planning for intelligent vehicles, compared and classified in [1], methods based on optimization and Model Predictive Control (MPC) can deal with challenges like constraints, moving obstacles, smoothness of paths, and uncertainties and have been adopted in many recent studies.

For MPC path planners, different prediction models have been considered in the literature. Some researchers use simple point-mass models which cannot properly emulate the vehicle's motion, especially at high speeds and severe maneuvers [2]. In the second group, linearized kinematic [3, 4] or dynamic [5,6] models of vehicles are used with satisfactory results and high computational efficiencies. The final group of studies uses nonlinear kinematic or dynamic vehicle models which are more precise, but impose a high

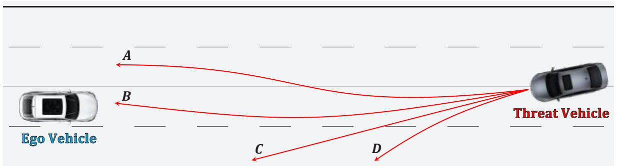

Fig. 1. Facing a deviated vehicle from the opposite lane and some of its possible and uncertain maneuvers.

computational burden and may need the reduction of prediction horizon or increase of sampling time [7, 8].

The main challenge of using MPC as a path planner in evasive maneuvers is to define collision avoidance constraints and three common approaches exist. The first approach which is more common consists of using linear constraints to decompose a non-convex region into convex sub-regions around the obstacles and solve the optimization problem in those sub-regions [2, 4, 6]. The second approach uses potential fields with the challenge of choosing suitable functions to precisely define the boundary of obstacles [3, 5]. The third approach uses distance functions to define nonlinear and non-convex constraints with high computational costs [7, 8]. Despite high fatalities of head-on collisions, the design of intelligent systems to avoid or mitigate such accidents has

*Corresponding author's email: ghaffari@kntu.ac.ir

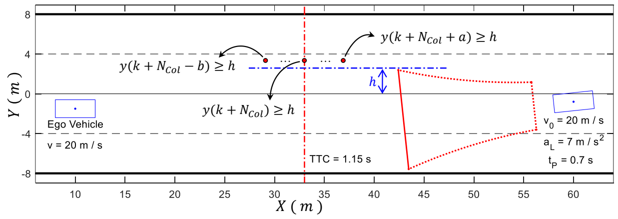

Fig. 2. Collision avoidance constraints on future lateral positions of ego vehicle.

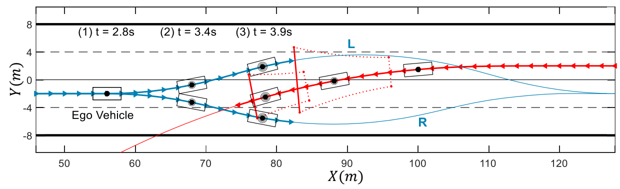

Fig. 4. Sensitivity of direction algorithm and two distinct paths for two close initial Conditions.

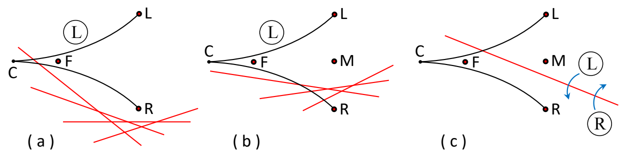

Fig. 3. Suitable swerve direction with respect to the motion line of the threat vehicle.

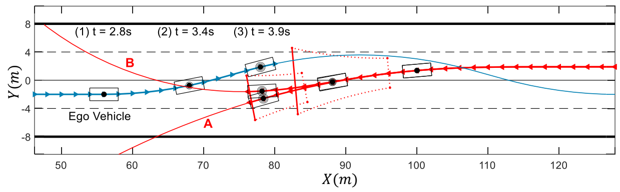

Fig. 5. Robustness of path planner to a sudden return with 0.7g lateral acceleration at a very close distance.

not yet been investigated and almost all researches in the field of collision avoidance are focused on avoiding rear-end collisions, pedestrians, and stationary obstacles on one way roads. So in the present study, an MPC path planner with a linear kinematic prediction model is designed, capable of calculating safe and maneuverable paths to avoid a head-on accident with a deviated vehicle from the opposite lane. Dealing with high uncertainty in the future motion of the threat vehicle is challenging and two novel approaches are investigated to choose a safe swerve direction and define linear collision avoidance constraints for this problem.

2- Methodology

2- 1- MPC algorithm

A linear kinematic bicycle model of vehicle [3,4] is considered and the following discretized state space model is used as the prediction model of MPC:

$$A_d = \begin{bmatrix} 1 & VT_S \\ 0 & 1 \end{bmatrix}, \quad B_d = \begin{bmatrix} \dfrac{(VT_S)^2}{L} \\ \dfrac{VT_S}{L} \end{bmatrix}, \quad C_d = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{1}$$

The model input is the angle of the front wheel and the state vector consists of lateral deviation and the heading angle of the ego vehicle with respect to the center line of the road. From Eq. (1), the sequence of future outputs and errors of the system can be simply derived, up to the prediction horizon and the quadratic cost function:

$$J = \vec{\mathbf{E}}_{\mathbf{k}}^T W_e \vec{\mathbf{E}}_{\mathbf{k}} + \vec{\mathbf{U}}_{\mathbf{k}}^T W_u \vec{\mathbf{U}}_{\mathbf{k}} \tag{2}$$

Can be defined. In Eq. (2), by rewriting the error vector based on future inputs, the constrained optimization problem can be formulated as follow:

$$\min_{\vec{\mathbf{U}}_{\mathbf{k}}} \frac{1}{2} \vec{\mathbf{U}}_{\mathbf{k}}^T H \vec{\mathbf{U}}_{\mathbf{k}} + f^T \vec{\mathbf{U}}_{\mathbf{k}} \quad , \quad s.t. \begin{cases} A . \vec{\mathbf{U}}_{\mathbf{k}} \leq b \\ lb \leq \vec{\mathbf{U}}_{\mathbf{k}} \leq ub \end{cases} \tag{3}$$

With inequality constraints on inputs/states and constraining lateral acceleration with bounds of inputs.

2- 2- Collision avoidance constraints

At each time step, first, a conservative motion prediction of the threat vehicle is calculated with a time horizon of 0.7 seconds and maximum lateral acceleration of $\pm 0.7g$. Then, the sample number of probable collisions (N_{Col}) is estimated, and the lateral positions of the ego vehicle around the sample N_{Col} are constrained to be outside of lateral space, occupied by the threat vehicle in 0.7 seconds (Fig. 2). If the estimated Time To Collision (TTC) is less than 0.7 second, the prediction horizon of threat vehicle reduces to TTC.

2- 3- Swerve direction algorithm

To choose the suitable swerve direction of evasive maneuver, it is suggested that the future feasible positions of the ego vehicle, get farther from the motion line of the threat vehicle. Two sequences of feasible positions, limited by the lateral acceleration of $\pm 0.7g$ for 1 second, are calculated for the ego vehicle and compared with each other, considering the motion line of the threat vehicle. Fig. 3 shows half of the possible cases for this approach.

3- Results and Discussion

To evaluate the performance of the system, two simulations are conducted, both simulating a close encounter with a relative distance of 45 meters at the beginning.

In the first simulation, the sensitivity of the direction algorithm is assessed. In this scenario, the threat vehicle enters the ego's lane with a lateral acceleration of $0.35g$, and the path of the threat vehicle and relative positions, make a critical case that puts the direction algorithm in a boundary situation. With a few centimeters of change in the initial lateral position of the threat vehicle, the direction algorithm can distinguish the difference and the planner can calculate separate paths to left and right for each initial condition (Fig. 4).

In the second simulation, the robustness of the path planner to severe direction change of threat vehicle at a very close distance is assessed. In this scenario, threat vehicle enters the ego's lane, same way as first simulation. But when the relative distance is around 22 meters, it suddenly returns to its lane with 0.7*g* lateral acceleration (Fig. 5, maneuver B).

4- Conclusions

The present study is focused on using linear MPC as a path planner for head-on collision avoidance. Dealing with high uncertainty in threat vehicle's motion is challenging and novel approaches are investigated to choose a safe swerve direction and define linear collision avoidance constraints for the problem. Simulation results show the robustness of the algorithm to sudden and highly accelerated (0.7*g*) deviations of threat vehicles, at very close distances. Moreover, the algorithm has a high sensitivity to choose suitable swerve direction and can calculate distinct safe paths to the left or right of the obstacle, with small changes in initial conditions.

References

[1] S. Dixit, S. Fallah, U. Montanaro, M. Dianati, A. Stevens, F. Mccullough, A. Mouzakitis, Trajectory planning & tracking for autonomous overtaking: state of the art and future prospects, Annual Reviews in Control, 45 (2018) 76-86.

[2] J. Nilsson, P. Falcone, M. Ali, J. Sjoberg, Receding horizon maneuver generation for automated highway driving, Control Engineering Practice, 41 (2015) 124-133.

[3] T. Idman, Path Planning and Trajectory Generation – Model Predictive Control, PhD Thesis, KTH Royal Institute of Technology, Stockholm, Sweden, (2019).

[4] S. Dixit, U. Montanaro, M. Dianati, D. Oxtoby, T. Mizutani, A. Mouzakitis, S. Fallah, Trajectory planning for autonomous high-speed overtaking in structured environments using robust MPC, IEEE Transactions on Intelligent Transportation Systems, 21(6) (2020) 2310-2323.

[5] Y. Rasekhipour, A. Khajepour, S.K. Chen, B. Litkouhi, A potential field-based model predictive path-planning controller for autonomous road vehicles, IEEE Transactions on Intelligent Transportation Systems, 18(5) (2016) 1255-1267.

[6] R. Hajiloo, M. Abroshan, A. Khajepour, A. Kasaiezadeh, S.K. Chen, Integrated steering and differential braking for emergency collision avoidance in autonomous vehicles, IEEE Transactions on Intelligent Transportation Systems, 22(5) (2020) 3167-3178.

[7] M. Obayashi, G. Takano, Real-time autonomous car motion planning using NMPC with approximated problem considering traffic environment, International Federation of Automatic Control, (2018) 279-286.

[8] J. Palatti, A. Aksjonov, G.Alcan, V.Kyrki, Planning for safe abortable overtaking maneuvers in autonomous driving, 2021 IEEE ITSC, (2021).

HOW TO CITE THIS ARTICLE
M. Abdollahi Nia, A. Ghaffari, S. Azadi, Head-on Collision Avoidance Path Planning with Model Predictive Control, Amirkabir J. Mech Eng., 54(8) (2022) 353-356.

DOI: 10.22060/mej.2022.20809.7321