Document Description: In order to begin writing my literature review, I have grabbed an example one from Model Fidelity Paper by ERsal, Stein, Jayakumar, and Liu. All of the cited sources are applicable to my literature review and therefore this will be the start of the literature review for me. I have grabbed all of the sources cited below and will write my own description of each below the reference citation on the next few pages. This will provide a literature review of the obstacle avoidance controller topic, but another smaller literature review will need to be done on modeling techniques, granular vehicle simulations, DEM, etc.

MPC Controller Literature Review

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This paper is concerned with obstacle avoidance in large AGVs at high speed with signi

\_cant vehicle dynamics-related constraints. Many obstacle avoidance algorithms have

been developed in the literature that allow for fast, continuous, and smooth motion of

the AGV among unexpected obstacles. Some early examples include the Arti\_cial Potential

Field method [3] [4], the Vector Field Histogram method [5] [6], the Dynamic

Window approach [7] [8], and the Curvature-Velocity method [9]. Reviews and comparisons

of these algorithms can be found in [10] [11] [12]. These algorithms were originally

developed for small ground robots and mainly focus on \_nding collision-free paths.

More recent research aims to improve the algorithms originally developed for small

robots and to adapt them to large AGVs at high speed. For example, Shimoda et al.

[13] combined Potential Field method and Dynamic Window technique to navigate a

high-speed AGV on rough terrain, avoiding discrete static obstacles and preventing dynamically

inadmissible maneuvers. Although computationally e\_cient, this method does

not guarantee feasibility or optimality [14].

To address the optimality problem, more rigorous methods have been pursued leveraging

the model predictive control (MPC) approach. MPC is a form of control in which the

control action is obtained by solving a \_nite horizon open-loop optimal control problem

over a receding horizon. MPC is a promising approach for obstacle avoidance due to its

capability of handling input saturation, system nonlinearity, and state constraints in a

dynamic environment [15].

Ogren and Leonard [16] proposed a way to combine the convergence-oriented Potential

Field method and the global Dynamic Window approach by casting these two approaches

in an MPC and control Lyapunov function framework [17]. They worked on a unicycle robot with a simple dynamic model. Tahirovic and Magnani [18] [19] provided an MPC

scheme with guaranteed closed-loop stability for nonlinear systems by incorporating a

passivity-based constraint [20]. The algorithm guarantees task completion and has the

potential to work with a broad class of vehicles and terrains. However, they assume that

the environment is completely known; that is, the locations of all the obstacles that the

vehicle may ever encounter are known a priori. In reality, only local information from

on-board sensors will be available and the vehicle will not be aware of the environment

beyond the sensor range.

Several other publications [21] [22] [23] [24] [25] [26] [27] [28] have also demonstrated

successful application of MPC to obstacle avoidance. There is also some research [29]

[30] [31] [32] [33] on MPC-based vehicle control techniques for car-like vehicles that

are related to the obstacle avoidance application. For example, the driver assistance

algorithm developed by Beal and Gerdes [33] used an a\_ne-force-input model to account

for tire nonlinearity and phase-portrait-based envelope boundaries to prevent the vehicle

from becoming unstable.

My Literature Review

Many obstacle avoidance algorithms have been developed in literature that allow for fast, smooth, and continuous motion around unexpected obstacles. These algorithms were primarily developed for small ground robots and mainly focus on finding collision free paths. However, they did not necessarily guarantee optimality or the vehicle’s ability to achieve the prescribed path. Some early examples of this research are the following:

Artificial Potential Field Methods:

[3] Khatib O. Real-time obstacle avoidance for manipulators and mobile robots. Int. J. Rob. Res.

1986;5:90-98

The philosophy of the potential field approach within the context of a manipulator avoiding obstacles can be summarized as:

The manipulator moves in a field of forces. The position or target to be reached is an attractive pole while all obstacles are repulsive surfaces for the manipulator parts. [3]

In this study, Khatib described the formulation and implementation of the artificial potential field concept towards obstacle avoidance. Using the kinematic relationships of the system to be controlled, a Lagrangian formulation is used to develop the equations of motion of the system. An artificial potential field is created that is nonnegative continuous and differentiable whose value goes to infinity as the vehicle approaches an obstacle. The overall artificial potential field is then a sum of the contributing potential fields caused by each of the obstacles within the obstacle field. Each of the obstacles are modeled as a composition of primitives with analytical equations representing their envelopes. Khatib successfully implemented this obstacle avoidance algorithm real-time in *Control in Operational Space of a Manipulator-with-Obstacles System* (COSMOS) with links and moving obstacles.

[4] Rimon E, Koditschek DE. Exact robot navigation using arti\_cial potential functions. IEEE Trans.

Rob. Autom. 1992;8:501-518

Rimon and Koditschek present a technique for constructing artificial potential-fields that bring a bounded-torque actuated robot to a desired configuration without hitting obstacles. Their formulation works for any n-DOF robot whose configuration space happens to be a generalized sphere world. As with [3], this method requires *a priori* knowledge of the topology of the obstacle field.

Vector Field Histogram Methods

[5] Borenstein J, Koren Y. The vector \_eld histogram - fast obstacle avoidance for mobile robots. IEEE

Trans. Rob. Autom. 1991;7:278-288

The vector field histogram (VHF) method allows the detection of unknown obstacles and avoids collisions as it steering a mobile robot to some end destination. The VHF method models the world as a two-dimensional Cartesian histogram grid and continuously updates this grid based on input on-board sensor data. The algorithm reduces the histogram to a one-dimensional polar histogram around the current robot location such that each sector of the polar histogram has polar obstacle density associated with it. The algorithm then selects the sector with a low obstacle density and aligns the robot’s steering with that sector. The VHF method outlined in this study successfully navigated a mobile robot through an obstacle field at an average speed of 0.6-0.7 m/s. This method is a local path planner, so there is no way of it purposefully following a globally optimal path. This algorithm may also result in the robot getting trapped in dead end situations.

[6] Gong J, Duan Y, Liu K, et al. A robust multi-strategy unmanned ground vehicle navigation method

using laser radar. Intelligent Vehicles Symposium; 2009.

Gong and Duan proposed a multistrategy navigation method to combat some common problems with autonomous vehicle navigation problems. The two common problems addressed are the vehicle reaching a local minimum and the vehicle navigating into a dead end. In both scenarios the vehicle remains stuck with many algorithms. The algorithm identifies the current state of the vehicle and determines what navigation strategy is best at the current moment. Vector Polar Histogram is used until the vehicle were to get stuck. The controller would then switch modes to wall-following, forcing the vehicle to find the wall and follow it until it is out of the dead end. Or if the vehicle is simply stuck at a local minimum, then the controller could switch to a move-towards goal mode if the vehicle is not blocked by obstacles. This would also apply to the situation where a vehicle’s path to the goal is clear, but the goal is right next to an obstacle and therefore preventing the Vector Polar Histogram Method from allowing that path as a possibility. This method was successful navigating a vehicle in both simulation and in real life at a top speed of 1 m/s.

Dynamic Window Approach

[7] Fox D, Burgard W, Thrun S. The dynamic window approach to collision avoidance. IEEE Trans.

Rob. Autom. 1997;4:23-33

Fox, Burgard, and Thrun focus specifically on the reactive avoidance of collisions with obstacles by a robot. A dynamic window approach is proposed deals with constraints imposed by velocity and acceleration limits. Steering commands are computed periodically thus avoiding the complexity of a general motion planning problem. First, they consider velocities that result in circular trajectories. Then, only velocities that can be reached within the next time window are considered, largely decreasing the search space forming the dynamic window. Admissible velocities are weighed with an objective function. In experiments, they were successful in navigating a B21 mobile robot up to 0.95 m/s.

[8] Brock O, Khatib O. High-speed navigation using the global dynamic window approach. IEEE In-

ternational Conference on Robotics and Automation; 1999.

Brock and Khatib proposed a global dynamic window approach to obstacle avoidance that combines path-planning and real-time obstacle avoidance algorithms to generate robot motions to complete a task and still remain safe in an unknown environment. As the robot moves through the environment, it builds an occupancy grid based off of sensor input data to represent the connectivity of free space. This allows the robot to learn about its environment without any global *a priori* knowledge of the obstacles. The global dynamic window approach combines the reactive collision avoidance of the dynamic window approach with a global, local minima-free navigation function NF1. An objective function is developed to choose the best path forward. This global dynamic window approach was successfully tested with a synchro-driven mobile robot Nomad XR4000 at 1.0 m/s.

Review and Comparisons of [3-9]

[12] Kunchev V, Jain L, Ivancevic V, et al. Path planning and obstacle avoidance for autonomous

mobile robots: a review. The Knowledge-Based Intelligent Information and Engineering Systems

Conference; 2006.

Kunchev, Jain, Ivancevic, and Finn present a review and comparison of the previously described techniques. Each obstacle avoidance method has its own benefits and disadvantages, but all need more development to be applied to a car-like vehicle at higher speeds.

More recent research aims to take these early collision avoidance algorithms and adapt them for the application of high speed AGV’s. The motion of these AGV’s is not as simple as the small robots the algorithms were initially developed for in that the AGV can not instantaneously move in any direction. Ignoring the effects of slip, an AGV will move in its heading direction. Some newer research into obstacle avoidance algorithms are the following:

combined Potential Field method and Dynamic Window technique

[13] Shimoda S, Kuroda Y, Iagnemma K. High-speed navigation of unmanned ground vehicles on uneven

terrain using potential \_elds. Robotica. 2007;25:409-424.

Shimoda, Kuroda, and Iagnemma proposed a potential field-based method of navigating an unmanned ground vehicle at high speeds across sloped and rough terrains. With this proposed method, a potential field is generated in a two dimensional trajectory space of the path curvature and longitudinal velocity. The potential field is generated based on dynamic constraints, terrain slopes, obstacle proximities, and the target location. A maneuver is selected within a set of performance bounds based on the local potential field gradient. Each maneuver is mapped to the low level commands necessary to execute that maneuver. This method has successfully been tested at a speed of 7 m/s.

[14] Koren Y, Borenstein J. Potential \_eld methods and their inherent limitations for mobile robot

navigation. IEEE International Conference on Robotics and Automation; 1991.

Shows the technique in [13] does not guarantee optimality.

This study presents a systematic overview of the downfalls of potential field methods. Four main drawbacks are noted and described in this study. First, a well-documented issue is trap situations due to local minima. Second, even though the controlled robot may be slightly smaller than a certain gap between two obstacles, the combined repulsive force from those two obstacles prevents the robot from passing through gaps it should be able to. Third, the robot motion exhibits oscillatory behavior near obstacles. This same behavior is seen in the fourth noted downfall where if a robot is moving through a narrow walled passage, the robot will oscillate close to each wall through the whole passage again due to the nature of the developed potential field and repulsive forces. For certain applications, potential field methods may be appropriate due to the simple, elegant, and quick navigation of the robot through the obstacle field. However, Rauth stability criterion presented in this study prove that this method would not be stable as vehicle mass and speed increase. These drawbacks have been experimentally proven and motivated a move by Koren and Borenstein away from potential field methods.

To address the issue of optimality, more rigorous approaches have been developed leveraging the Model Predictive Control approach. With this method, control action is obtained by solving a finite horizon open-loop optimal control problem over a receding horizon.

[15] An Introduction to Nonlinear Model Predictive Control

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This is a very important source and presents some nonlinear model predictive control formulation and background. This source can be used in the MPC history section as well. Basically though, NMPC methods are being explored due to its ability to incorporate design driven constraints into the robot control. As time goes on, our systems are becoming subject to more safety and environmental constraints making the application of previous methods tough. With NMPC it is not too difficult to add more system constraints to the optimal control problem solved each time step. This source outlines some stability and feedback considerations of the NMPC methods and presents some different methods of applying the NMPC method as well as solving the optimal control problem in each time step.

MPC is a promising approach for obstacle avoidance due to its capability of handling input saturation, system nonlinearity, and state constraints in a dynamic environment.

[16] Ogren P, Leonard NE. A convergent dynamic window approach to obstacle avoidance. IEEE Trans.

Rob. 2005;21:188-195.

[17] Primbs JA, Nevisti V, Doyle JC. Nonlinear optimal control: a control Lyapunov function and re-

ceding horizon perspective. Asian J. Control. 1999;1:14-24.

[18] Tahirovic A, Magnani G. Passivity-based model predictive control for mobile robot navigation plan-

ning in rough terrains. IEEE/RSJ International Conference on Intelligent Robots and Systems;

2010.

[19] Tahirovic A, Magnani G. General framework for mobile robot navigation using passivity-based MPC.

IEEE Trans. Autom. Control. 2011;56:184-190.

[20] Ra\_ T, Ebenbauer C, Allgower P. Assessment and Future Directions of Nonlinear Model Predictive

Control: nonlinear model predictive control: a passivity-based approach. Berlin: Springer; 2007.

Studies showing successful application of the MPC Obstacle Avoidance Controller Technique

[21] Park JM, Kim DW, Yoon YS, Kim HJ, Yi KS. Obstacle avoidance of autonomous vehicles based

on model predictive control. J. of Automobile Eng. 2009;223:1499-1516.

[22] Bevan GP, Gollee H, O'Reilly J. Trajectory generation for road vehicle obstacle avoidance using

convex optimization. J. of Automobile Eng. 2010;224:455-473.

[23] Nanao M, Ohtsuka T. Nonlinear model predictive control for vehicle collision avoidance using

C/GMRES algorithm. IEEE International Conference on Control Applications; 2010.

[24] Gao Y, Lin T, Borrelli F, et al. Predictive control of autonomous ground vehicles with obstacle

avoidance on slippery roads. Dynamic Systems and Control Conference; 2010.

[25] Gray A, Gao Y, Lin T, et al. Predictive control for agile semi-autonomous ground vehicles using

motion primitives. American Control Conference; 2012.

[26] Abbas MA, Eklund JM, Milman R. Real-time analysis for nonlinear model predictive control of

autonomous vehicles. IEEE Canadian Conference on Electrical & Computer Engineering; 2012.

[27] Frasch JV, Gray A, Zanon M, et al. An auto-generated nonlinear MPC algorithm for real-time

obstacle avoidance of ground vehicles. European Control Conference; 2013.

[28] Jeon JH, Cowlagi RV, Peters SC, et al. Optimal motion planning with the half-car dynamical model

for autonomous high-speed driving. American Control Conference; 2013.

Studies into MPC-based techniques for car like vehicle collision avoidance

[29] Falcone P, Borrelli F, Asgari J, et al. A model predictive control approach for combined braking

and steering in autonomous vehicles. Mediterranean Conference on Control & Automation; 2007.

[30] Canale M, Fagiano L. Vehicle yaw control using a fast NMPC approach. IEEE Conference on

Decision and Control; 2008.

[31] Anderson SJ, Peters SC, Pilutti TE, Iagnemma K. An optimal-control-based framework for tra-

jectory planning, threat assessment, and semi-autonomous control of passenger vehicles in hazard

avoidance scenarios. Int. J. Veh. Auton. Syst. 2010;8:190-216.

[32] Gray A, Ali M, Gao Y, Hedrick JK, Borrelli F. A uni\_ed approach to threat assessment and control

for automotive active safety. IEEE Trans. Intell. Transp. Syst. 2013;14:1490-1499.

[33] Beal CE, Gerdes JC. Model predictive control for vehicle stabilization at the limits of handling.

IEEE Trans. Control Syst. Technol. 2013;21:1258-1269.