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.

Ogren and Leonard present the Dynamic Window Approach for fast and safe obstacle avoidance in unknown environments and recast the approach in a continuous nonlinear framework, drawing many similarities to Model Predictive Control. A method for generating a navigation function with a single unique minima is presented. In this study, the control input space is discretized for a computationally tractiable version of MPC and exhaustive search is used to identify the best control input choice. Of all the control input possibilities, there always exists one such that the robot will be able to stop before hitting any obstacle to insure safety.

[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.

Primbs, Nevisti, and Doyle explore Control Lyapunov Functions (CLF) and Receding Horizon Control or MPC approaches to non-linear control. Comparisons are made between the two methods and it is noted that they each seek to solve the same problem optimally and some properties of each method are complementary to one another. The CLF methods are best interpreted in the context of Hamilton-Jacobi-Bellman equations while MPC relates more closely to a Euler-Lagrange Framework. CLF provides a global optimal solution, but the partial differential equation one must solve is very difficult and computationally infeasible. The MPC approach instead allows for on-line computation of an optimal solution locally, and resolves this problem every time step specified. The problem is only solved over a fixed time horizon. However, it is difficult to the apply Lyapunov Stability Theory to this MPC method where numerical techniques are used to solve for optimal solutions. Also, the relation between time horizon length and stability are not necessarily linear as noted by simulation results in this paper. Two hybrid CLF MPC methods are proposed at the end of this paper.

[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.

Tahirovic and Magnani propose a passivity based MPC control for Robot Navigation through rough terrain. This method boasts simplicity of application for all vehicles as long as one can accurately model them. A virtual model of the vehicle is then made using shaped energy. The algorithm quantifies roughness of the terrain and uses this parameter when analyzing the cost of a specified path. For this study, the roughness in this study is expressed as the relative height of the terrain locally. Simulations have proven successful navigation of a vehicle through a hilly terrain, yet there is no mention of physically how terrain data would be obtained. This PB/MPC method can be applied on-line, but this is only feasible if there is some sort of sensor and analysis algorithm which can sense the local terrain roughness.

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

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

Tahirovic and Magnani present a more generalized framework in this study than the one above and show the successful simulation of a unicycle through an obstacle field and a car-like vehicle as well.

Studies showing successful application of the MPC Obstacle Avoidance Controller Technique

[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.

Bevan, Gollee, and O’Reilly propose a new method for trajectory generation for raod vehicle obstacle avoidance using convex optimization. The dynamics of a vehicle is a very nonlinear case which on the surface poses a non-convex optimization problem when searching for an optimal path trajectory. This study uses their method on a vehicle performing an aggressive double lane change maneuver with the intent of designing a quick emergency obstacle avoidance algorithm for when cars either need to stop immediately or turn to move around the incoming obstacle. Most avoidance systems solely slow the vehicle down to prevent collision with a hazard in the vehicle heading direction. The optimization is performed in three stages in which each stage includes different assumptions to frame the problem as a convex optimization problem. The first stage solves for a trajectory assuming no slip, the second assumes slip but constant speed, and the third uses the values from previous runs to insert to non-convex expressions and hold them constant. This study successfully simulated a general wheeled vehicle performing an optimal double lane change maneuver.

They also have a good discussion about modeling, simulation copied below:

Richard Hamming said that the purpose of computing

is insight, not numbers [7]. This applies directly

to model development. All models are an abstraction

of reality. The appropriate level of abstraction depends

on the intended purpose.

Detailed analysis of vehicle performance requires

high-fidelity models. Dynamicists often use sophisticated

representations of tyre behaviour (e.g. references

[8] to [11]) and account for effects such as load

transfer under braking and cornering (e.g. references

[12] to [14]).

Control engineers also make use of models, and

good control systems often encompass a description

of the dynamics that they are designed to regulate.

However, the level of abstraction is usually higher.

Feedback mechanisms can account for modelling

approximations. Thus control engineers often work

with linearizations and other simplifications (e.g.

references [15] to [17]).

The development of reference inputs is one step

removed further still. If the aim is to develop a

feasible trajectory, i.e. one that the vehicle is capable

of tracking accurately, it is necessary to consider the

overall constraints on its behaviour. But it is not

necessary to consider in detail how those constraints

arise or how the control system might follow that

trajectory.

7 Hamming, R. W. Numerical methods for scientists

and engineers, 2nd edition, 1973 (McGraw-Hill).

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

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

Nanao and Ohtsuka present a nonlinear MPC algorithm which finds a solution using continuation/generalized minimal residual (C/GMRES) algorithm to find a solution. The algorithm was tested successfully in simulation and though runtimes are not yet quick enough for physical realtime implementation, they are close to expect it in the near future of this paper. Tire ground interactions are modeled using the Pacejka Magic Formula. A friction circle is used to quickly determine the maximum friction force able to be generated and this is used to create an “unavoidable region” in which the vehicle is unable to avoid hitting the obstacle. However, this method relies heavily on accurate modeling of the ground tire interactions.

[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.

Gao, Lin, Borrelli, Tseng, and Hrovat present and test two different MPC algorithms for obstacle avoidance. The first algorithm is a one level MPC algorithm. The algorithm combines the reuirements of obstacle avoidance and optimal trajectory planning into one step, solving a highly nonlinear optimal control problem within the horizon each time step. The objective function includes a proximity term which increases as the vehicle gets closer to an obstacle. The second algorithm is a two-level approach. A high-level path planner calculates an optimal trajectory for the vehicle disregarding any obstacle information. A low level algorithm then calculates the optimal control inputs that both route the vehicle around obstacles and maintain the vehicle along the desired trajectory. While both algorithms were implemented in realtime successfully on icy road performing a double lane change maneuver, the two-level approach was successful at speeds of 55 kph while the one level could only be implemented up to 40 kph. Computational runtimes were compared and show the two-level approach runs much quicker than the one-level approach and shows promise for hierarchical MPC methods in the future.

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

motion primitives. American Control Conference; 2012.

The proposed method in this source builds upon the two-level approach in the above source, but identifies the issue of the vehicle model predicting infeasible trajectories for the vehicle in the high level planner. Instead, in this source motion primitives are used to develop a high-level trajectory assembled from trims which are connected by maneuvers. Possible trims are straight, left turn, right turn, drift left, and drift right. Possible maneuvers which connects two trims include straight to left turn, left to straight, straight to drift, etc. This method proved successful in simulation. In experiment, the vehicle was capable of avoiding an obstacle on icy roads as well, but the speeds of this success are not mentioned.

[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.

Abbas, Eklund, and Milman analyzed the possible realtime implementation of a nonlinear MPC algorithm for obstacle avoidance using Simulink and simulating the vehicle as a full Carsim nonlinear multibody vehicle. Offline a trajectory is generated guiding the vehicle from a start point to the desired end location. Then on-line each controller time step a cost function is used to weigh possible trajectories and deviation from the reference trajectory are penalized. A pointwise potential function is used to increase cost as the vehicle gets closer to any obstacle. Simulation results showed that the vehicle is capable of navigating around a single obstacle. The cost function is minimized using the gradient descent optimization method. The amount of time to find an optimal path in the simulation varies depending on the scenario the vehicle is in in each time step. A vehicle in close proximity to an obstacle will take longer to pick a best path than a vehicle in free space pointed towards the goal. Warm starting is used during the optimization routine to help quicken the optimization process, but there are still many time step scenarios where the amount of time needed to calculate a best path exceeds the controller time step.

[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.

The authors of this paper propose a nonlinear MPC Algorithm for real-time obstacle avoidance that uses the software ACADO to autogenerate C-code to perform the high level trajectory planning code. This increases algorithm speeds to the point where even with a complicated vehicle model, nonlinear tire model, and wheel dynamics considered, this proposed method was able to perform computations quick enough to control a vehicle real-time at 10 m/s. Simulations are performed on rigid flat ground.

[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.

In this paper, the authors propose a fast motion planner that uses a half-car dynamical model for a wheeled vehicle. A fast local steering algorithm is developed to increase runtimes and splits into a geometric path planning step and then an optimal time parameterization step. The three control inputs in this study are steering angle, and the longitudinal slips of the front and rear tires much like a rally car driver. Simulation results support the real-time implementation of a controller using this obstacle avoidance algorithm. It operates quick enough to operate in real-time.

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.

A MPC algorithm was developed that controls braking and steering to better control a vehicle during a double lane change maneuver. This study has shown their algorithm performs better than an algorithm controlling steering alone on a snowy road. The ability of the controller to slow down the vehicle assists with vehicle navigation.

[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.

These authors use a model predictive controller to maintain driver safety by keeping them in their lane. The control itself has an internal 4 wheel vehicle model as well as a driver model, allowing the controller to predict what the driver will command. The controller aims to minimize control input so that only when the driver is in danger say departing from the lane will the controller take action. Otherwise, it seeks to maintain safety constraints so that the controller only intervenes when it predicts the safety constraints maybe violated. Simulation results proved successful, but when implemented in real life at a Volvo facility, the only issue was minor breaking of a safety constraint. This however was due to sensor delay and in the future this delay should be accounted for in the algorithm.

[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.

This paper proposed a solution to the issue of vehicle stabilization control near the limits of handling. Normally, an ESC works by using a linear model of a vehicle to predict driver intent and when the vehicle deviates past a threshold of the allowed deviation between driver intent and vehicle behavior, then the controller activates and stabilizes the vehicle. However, this method does not work when the vehicle is being operated near the stable vehicle limits such as by an experienced driver because the linearized vehicle model is linearized about a conservative point for production level cars. The vehicle behavior near its dynamic limits are nonlinear and do not match the linearized model. Therefore, an MPC based controller was proposed and tested that operates at two levels and quick enough for real-time implementation. The controller has two objectives. The first is to keep the vehicle inside of the safe-handling envelop and respond appropriately in case the vehicle leaves this safe envelop. The second objective is to allow the controller to track the driver’s intended trajectory. Overall the controller is able to successfully achieve these objectives in experiments with Stanford’s PI vehicle testbed. +