Trajectory Planning of an Autonomous Vehicle in Multiple-Vehicle Traffic Scenarios

Mahdi Morsali

Linköping Studies in Science and Technology

Dissertations, No. 2126

Trajectory Planning for an Autonomous Vehicle in Multi-Vehicle Traffic Scenarios

Mahdi Morsali

Linköping University
Department of Electrical Engineering
Division of Vehicular Systems
SE-581 83 Linköping, Sweden

Linköping 2021

This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

<https://creativecommons.org/licenses/by-nc/4.0/>

Edition 1:1

© Mahdi Morsali, 2021

ISBN 978-91-7929-693-3

ISSN 0345-7524

URL <http://urn.kb.se/resolve?urn=urn:nbn:se:liu:diva-173940>

Published articles have been reprinted with permission from the respective copyright holder.

Typeset using X_YTEX

Printed by LiU-Tryck, Linköping 2021

ای پادشاه خوبان داد از غم تنهایی

دل بی توبه جان آمد وقت است که باز آیی

O the king of all kindnesses, souls are in grief of living without you,
Hearts have stopped beating, it's time to come back

Hafez

To My Family

POPULÄRVETENSKAPLIG SAMMANFATTNING

Stora industriella och akademiska framsteg samt investeringar har gjorts för att möjliggöra autonoma fordon, men det finns fortfarande många problem som behöver vidare analys, utforskas, och testas innan säker och tillförlitlig autonom körning är en realitet i vardagen.

Den här avhandlingen behandlar automatisk planering av autonom körning i olika trafiksituationer, vägförhållanden, och för olika fordon. Huvudsakliga aspekter att ta hänsyn till är beräkningskomplexitet, säkerhet, och komfort hos passagerare. Algoritmer utvecklade i den här avhandlingen är utvärderade i simulering med multipla fordon att ta hänsyn till. Resultaten faller i huvudsak i två delar, där den första behandlar planering i spatio-temporal domän där bana och hastighet planeras simultant. Här beskrivs specifikt hur olika taktiska beslut kan automatiseras baserat på fordonets tillstånd och omgivande fordonets beteende. Den andra delen utforskar särkopplad planering där särskilt fokus är på hastighetsplanering.

För ett autonomt fordon så är ofta vägnätet känt via tillgängliga kartor vilket kan användas för att förbättra effektivitet vid planering. Första delen av avhandlingen fokuserar på detta, att planera kollisionsfria banor i mer komplexa trafiksituationer i en spatio-temporal domän. Spatio-temporal planering har fördelar jämfört med särkopplad planering, men där också sökrymden blir stor vilket ger komplexitetsproblem vid sökning. En viktig del av avhandlingen är utveckling av metoder, baserade på Support Vector Machines (SVM), för att förenkla sökproblemet och göra planeringen mer effektiv. En SVM klassificerar omgivande fordon och räknar effektivt ut en säker korridor för fordonet att söka i. Detta görs genom att först lösa ett konvext optimeringsproblem, givet information om start- och slut-punkt, samt stationära och rörliga hinder. Detta, tillsammans med egenskaper hos den framräknade korridoren, gör att komplexa planeringsproblem kan lösas på ett effektivt sätt och ge säkra lösningar.

Speciellt intressant är tunga fordon som är mer känsliga än personbilar för väglutning, vägens krökning, och fordonets karakteristik när fordonets bana och hastighet planeras. Ett tungt fordon kan lätt hamna i ofördelaktiga situationer även vid låga hastigheter och därför behöver accelerationer, krafter, och andra säkerhetsrelaterade begränsningar tas i beaktning när hastighet planeras. Simulering av realistiska trafiksituationer som rondellkörning, korsningar, samt omkörningsmanövrar med multipla fordon utvärderas i avhandlingen och jämförs med optimala manövrar vilka är beräkningsmässigt betydligt mer krävande. Analyserna visar på god prestanda för föreslagna metoder samt att lösningarna jämför sig väl med optimala manövrar och hittar säkra och komfortabla lösningar.

ABSTRACT

Tremendous industrial and academic progress and investments have been made to progress autonomous driving, but still many aspects are yet to be analyzed, researched, and tested, until safe and reliable autonomous driving is an everyday reality.

This thesis deals with planning of autonomous vehicles in different urban scenarios, road, and vehicle conditions. Main concerns in designing the planning algorithms, are real time capability, safety and comfort. The research conducted in this thesis falls mainly into two parts, one part investigates decoupled trajectory planning algorithms with a focus on speed planning, and the other explores different coupled planning algorithms in the spatio-temporal domain where path and speed are planned simultaneously. Additionally, a behavioral analysis is carried out to evaluate different tactical maneuvers the autonomous vehicle can have considering the initial states of the ego and surrounding vehicles.

Particularly relevant for heavy duty vehicles that has to be considered when planning a safe speed are road conditions such as banking, friction, road curvature and vehicle characteristics. A heavy vehicle might end up in an unfavorable, or even dangerous state even at low speeds and therefore vehicle constraints on acceleration, jerk, steering, steer rate limitations and other safety limitations such as rollover are further considerations in speed planning algorithms.

For an autonomous vehicle, the structure of the road network is known to the vehicle through mapping applications. Therefore, this key property can be used in the planning algorithms to increase efficiency. A major part of the thesis, is focused on handling moving obstacles in a spatio-temporal domain and collision-free planning in complex urban structures. Spatio-temporal planning holds the benefits of exhaustive search and has advantages compared to decoupled planning, but the search space in spatio-temporal planning is complex. A key part of this thesis are methods to utilize support vector machines to simplify the search problem and make the search more efficient. An SVM classifies the surrounding obstacles into two categories, left and right, and efficiently calculate an obstacle free region for the ego vehicle. The formulation achieved by solving the SVM optimization problem, provides information about the initial point, destination, stationary and moving obstacles. These features, combined with a smoothness property of the Gaussian kernel used in the SVM formulation is proven to be able to solve complex planning missions in a safe and efficient way.

Different road conditions with large banking, low friction and high curvature, and vehicles prone to safety issues, specially rollover, are evaluated to calculate the path and speed profile limits. Simulation of realistic driving scenarios such as roundabouts, intersections and takeover maneuvers with multiple moving vehicles as obstacles are tested and compared to optimal path and speed profiles to investigate the performance of the proposed algorithms.

Acknowledgments

First and foremost, I would like to express my sincere gratitude to my advisor, Erik Frisk, for his continuous support of my Ph.D. study as well as his patience, motivation, enthusiasm, and immense knowledge. His guidance helped me throughout the research and writing of this thesis. Erik is further acknowledged for being supportive outside work, too.

I would like to acknowledge the valuable input of my co-supervisor, Jan Åslund, who contributed to many discussions and helped shape this dissertation. Lars Nielsen is acknowledged for giving me the opportunity to start as a research engineer in vehicular systems. Lars Eriksson, as my examiner in my Master's thesis, course teacher, and colleague in our teachings, is acknowledged for both his patience and his guidance over these years.

Special thanks go to my friend and colleague, Iman Shafikhani, who is always available for short talks and long walks around the university. He is an openminded, lighthearted, and responsible person and, of course, a true friend.

I wish to thank my officemates Kristoffer Ekberg and Kristoffer Lundahl for their companionship, empathy, and encouragement.

I would also like to thank my dear friends, Dr Yazdi, Mohammad Amin, Ruhollah, Fatemeh, Shervin, Meysam, Mohammad Hossein and many others, for remaining supportive and for giving me many, many things to enjoy outside my Ph.D.

I must express my profound gratitude to my dear wife, best friend, and partner, Soheila Aeeni, for providing me with unwavering support and continuous encouragement throughout my studies. This accomplishment would not have been possible without you. Thank you **Soheila!**

Finally, I would like to thank my dear parents and sweet sister for supporting and encouraging me throughout my life.

Contents

Abstract	vii
Acknowledgments	ix
Contents	xi
1 Introduction	1
1.1 Autonomous Vehicles	1
1.2 Properties of Proposed Planning Algorithms	3
1.3 Coupled and Decoupled Trajectory Planning	5
1.4 Behavioral Analysis	8
1.5 Proposed Trajectory Planning Algorithms	9
1.6 Summary and Contributions of Included Papers	12
1.7 Conclusions and Future Work	18
Bibliography	21
2 Paper I	29
2.1 Introduction	30
2.2 Methodology	32
2.3 Collision Free Regions in Search Space	33
2.4 Trajectory planning	37
2.5 Results and Discussion	48
2.6 Conclusion	57
References	59
3 Paper II	65
3.1 Introduction	66
3.2 Background for Planning using SVM	68

3.3	Collision-Free Trajectory Computation	70
3.4	Results and Discussion	78
3.5	Conclusion	83
	References	87
4	Paper III	91
4.1	Introduction	92
4.2	Trajectory Planning	93
4.3	The collision free corridor	95
4.4	Path and Speed Planning	98
4.5	Results and Discussion	102
4.6	Conclusions	104
	References	108
5	Paper IV	113
5.1	Introduction	113
5.2	Problem Formulation	115
5.3	Modeling Roll Dynamics	116
5.4	Path and Velocity Optimization	121
5.5	Results and Discussion	127
5.6	Conclusions	129
	References	130
6	Paper V	135
6.1	Introduction	136
6.2	Path Planning	138
6.3	Speed Planning	142
6.4	Results and Discussion	149
6.5	Conclusions	161
	References	164

A decorative graphic consisting of several thin, vertical black lines of varying heights, positioned to the left of the chapter title.

1

Introduction

1.1 Autonomous Vehicles

Autonomous vehicles (AVs) have gained significant attention in recent years as a possibly important factor in fulfilling sustainable development goals (Lim et al., 2018). AVs provide a, possibly important part of a solution to transport related problems such as air pollution, congestion and reducing accidents (Acheampong et al., 2021). Less stressful driving experience, reduced number of deaths due to reduced number of accidents, increased productivity and better fuel economy are other advantages that may be possible to achieve through vehicle autonomy (Pettigrew et al., 2018; Stern et al., 2019; Woldeamanuel et al., 2018). Survey statistics estimate that 94 percent of accidents are caused by humans, and only 6 percent caused by vehicle failure, environmental reasons and unknown reasons (Singh, 2015). With human errors as a main cause of accidents, autonomy may significantly reduce accidents and reduce death rate. With efficient control strategies, autonomous vehicles can predict traffic and smooth speed profiles also have the potential to reduce fuel consumption and emissions (Mersky et al., 2016).

By 2050, more than 60 percent of world population are expected to live in cities (Lim et al., 2018) and autonomy is realized to be a solution to reach

sustainable cities by smart traffic management. However, studies on readiness indexes of cities, such as policy and regulation, physical infrastructure and cyber infrastructures, indicate that cities are far from ready (Khan et al., 2019) in integrating the technology. Complex technology, liability, ethics and many other parameters are challenges that AVs face and influence production of AVs by automotive companies (Bagloee et al., 2016; Martínez-Díaz et al., 2018).

Among technological challenges facing AVs, some are related to challenges in connection to the other vehicles and infrastructures (Bagloee et al., 2016; Lu et al., 2014) and some are central to the ego vehicle (Buehler et al., 2009). Correct decision making in AVs is a main challenge that is central to the ego vehicle, and includes, vehicle safety and comfort, design of time and fuel efficient algorithms, reliability, real time performance, etc (Chu et al., 2015; Elbanhawi et al., 2015; Taeihagh et al., 2019).

This thesis focuses on decision making and control of the EGO vehicle and an architecture of the decision making steps of an autonomous vehicle, can be divided into mainly four steps: route planning, behavioral analysis, motion planning, and local control (Paden et al., 2016) as illustrated by Figure 1.1. The route planning step, as the highest level in the hierarchy, calculates a route based on the vehicle start and destination and road network to show which directions to take. A behavioral step, that is made by perceiving the surrounding environment of the ego vehicle and other vehicles involved in the traffic, chooses an appropriate driving behavior. An AV requires many sensors assessing the immediate environment, for example cameras, Lidar, radar, sonar and IMU sensors to make a sound perception of the surrounding environment and decide appropriate behavior for the ego vehicle (Kocić et al., 2018). When a higher level behavioral step, based on the perception made through sensors and cameras, chooses the appropriate behavior for the vehicle, a motion planning step should calculate a kinematically feasible path and trajectory to move the vehicle from start point to the destination in a safe, collision free, and comfortable way. A trajectory planner, in addition to the spatial information, includes temporal information (speed and acceleration profile) of the ego vehicle that determines how the vehicle should travel in the calculated path (Pham, 2015).

Figure 1.1 illustrates, a simplified hierarchy of the decision making steps, where the blue highlighted steps, the behavioral analysis and motion planning are the main concerns in this thesis. The main objective of this thesis is the

Figure 1.1: Decision making hierarchy in an autonomous vehicle.

development of safe and comfortable trajectory planners for a non-holonomic autonomous vehicle, where the developed algorithms are central to the autonomous vehicle. In the next sections, objectives and motivations for the problems in trajectory planning in multi-vehicle scenarios are explained.

1.2 Properties of Proposed Planning Algorithms

Critical features in designing a trajectory planner for an autonomous vehicle, are safety, comfort, real time calculation, optimality and general applicability. The following sections introduce important problems, the motivation and objectives in designing trajectory planning algorithms and then in Section 1.6, contributions of included papers are explained and related to these identified problems.

Safety

Vehicle safety includes broad range of criteria and is standardized under ISO 26262 as road vehicles and functional safety (ISO26262, 2018). It is assumed that the studied vehicles have standard mechanical properties and safety is further explored in algorithmic development of path and speed planners.

First and foremost, the main safety requirement on the trajectory planner is to avoid collisions with surrounding traffic and infrastructure. A more detailed discussion on collision avoiding techniques in multiple-vehicle scenarios is provided in Section 1.3 and Section 1.4. Additionally, especially when considering heavy-duty vehicles, major safety requirements applied on the speed planner are rollover prevention (Hu et al., 2019) and skidding (Han et al., 2014; Low et al., 2008). One interesting question is how detailed models are required to avoid dangerous roll behavior in heavy duty vehicles (Shim et al., 2007), especially since that depends not only on speed and curvature of the paths, but also on road conditions like banking (Guizhen et al., 2016). In Figure 1.2, a simplified roll model with influencing road and vehicle characteristics is illustrated. The vehicle characteristics such as roll center, vehicle

width and center of gravity, and road characteristics such as banking, friction and curvature all influence what paths and speeds that are feasible and safe. In the thesis, influence from these factors are explored on computation of path and speed profiles.

Figure 1.2: A simplified roll model in a banked road.

Comfort

To avoid abrupt changes in speed and unwanted steering maneuvers, comfort requirements are to be considered in calculation of path and speed profiles. The calculated paths should be kinematically feasible with controlled curvature (Zhou et al., 2020) and the speed profile should restrict the lateral and longitudinal motion (Kuderer et al., 2015). To be more specific, lateral and longitudinal jerk, acceleration and velocity should be restricted to a comfort zone to achieve a smooth speed profile (Du et al., 2016; He et al., 2020; Kuderer et al., 2015). Here, the proposed methods use comfort as one of the main design criteria in planning approaches.

Computational Complexity

Trajectory planning is computationally expensive, and to achieve real-time performance it is relevant to see how planning complexity can be reduced. Using lane network for sampling (Ziegler et al., 2009) or informative heuristics (Likhachev et al., 2009), are examples of approaches proposed by researchers to cope with planning complexities arisen from road structure or

added numbers of obstacle vehicles. Here, to achieve a real-time performance, improvements on planning such as reduced search space for planning, a new heuristic, pruning techniques in search and reduced physical model complexity are explored.

Near Optimal Solutions

Optimal control trajectory planning, due to the limitations in formulation of obstacles with non-convex shapes and long calculation time, are often not suitable for real time planning. Solving general optimization problems is still a research question and may not be trusted as a general planning approach (Bai Li et al., 2017). However, optimal control planning is used for offline calculation of kinematically feasible motions and to store in a lookup table for online motion planning (Bottasso et al., 2008; Grymin et al., 2014; Bai Li et al., 2017). Furthermore, optimal control as a tool can be used to evaluate and compare the results obtained with search algorithms in simplified simulation scenarios. In this thesis, optimal control planning is widely used in calculation of offline motion primitives and to evaluate the performance of the proposed planning approaches.

Algorithm Generality and Robustness

For a planning algorithm to be reliable, it needs to be tested in various planning problems and cope with complexities such as road network and multiple vehicles. Therefore, an important feature that is necessary for a planner, is general applicability and robustness of the proposed algorithms. In a particular driving scenario, adding randomness in initial position, speed and numbers of the moving obstacles in the surrounding environment is one way to test planning algorithms (Luders et al., 2010).

To evaluate this property in the proposed algorithms, complex and different scenarios, added numbers of obstacle vehicles, and uncertainty in the surrounding environment are used in simulations.

1.3 Coupled and Decoupled Trajectory Planning

One way to categorize trajectory planning algorithms are, decoupled and coupled trajectory planning. Decoupled planning here means that path and velocity are computed as separate steps, and not simultaneously as in coupled

trajectory planning. In Figure 1.3, a schema of a decoupled planning algorithm is illustrated. A decoupled planner in general is known to be faster compared to a coupled speed and path planning (Den Berg et al., 2009). In (Zhu et al., 2020), a decoupled trajectory planning approach in a highly dynamic environment is developed using parameterized curvature control. However, certain planning scenarios are challenging to solve with decoupled planning. In Figure 1.4, a planning problem with two robots and intended traveling directions are introduced (LaValle, 2006). While this problem can be solved with a coupled planning approach, due to fewer degrees of freedom (Den Berg et al., 2009), it can be a challenge for a decoupled planning approach. The vehicle C_1 to travel from point A to B needs temporal information of vehicle C_2 and in a prioritized planning the completeness is lost if one vehicle neglects the motion of the other vehicle.

Figure 1.3: A schema of the model predictive controller.

Figure 1.4: A planning problem with vehicle C_1 aiming to travel from A to B and vehicle C_2 from B to A.

In another overtaking scenario shown in Figure 1.5, a prioritized planning (decoupled approach) sees other obstacles with higher priority compared to the ego vehicle. In this problem, the planner does not have a solution since the vehicle to be overtaken is planned to travel earlier. Furthermore, due

to the smaller state space, the planning limits reach earlier with a decoupled planning (Boyuan Li et al., 2018). An advantage of coupled planning conducted in spatio-temporal environment is easy consideration of dynamic moving obstacles and uncertainties in planning (Yoo et al., 2018).

Figure 1.5: An overtaking challenge for decoupled planning.

Collision Avoidance in Multiple-Vehicle Scenarios

Coupled or decoupled planning approaches use different strategies in collision avoidance. In decoupled planning approaches, static obstacles are avoided by the path planner and moving obstacles are avoided by the speed planner. In an example shown in Figure 1.6, the configuration space is shown with black regions as stationary obstacles, red and blue curves as the paths of moving obstacles and green curve as the ego vehicle's path. The stationary obstacles as illustrated are avoided with a path planner and the moving obstacles are mapped into a distance time graph of the ego vehicle as illustrated in Figure 1.7. In the figure, red and blue blocks are position of moving obstacles in distance-time graph of an ego vehicle, corresponding to the moving obstacle shown in red and blue paths in Figure 1.6 and a speed planner calculates green trajectory for the ego vehicle by avoiding the moving obstacles.

In coupled planning approaches, considering the velocity and acceleration of the obstacles, time evolution of the obstacles are calculated in spatio-temporal environment. In Figure 1.8(b), an example of a coupled trajectory planning in an overtaking scenario, shown in Figure 1.8(a), is illustrated where the red blocks represent the time evolution of the moving obstacles, transparent red surfaces represent solid lines used to define the road and the red trajectory is the trajectory calculated for the ego vehicle in an obstacle-free corridor defined by blue surfaces in spatio-temporal environment. The spatio-temporal plot is an extension to distance-time plot where both x and y coordinates are included and the planner by avoiding obstacle regions, calculates path and speed profiles simultaneously.

Figure 1.6: A configuration space with black regions as stationary obstacles, red and blue curves as the path of moving obstacles and green curve as ego vehicle's path.

1.4 Behavioral Analysis

Representing the environment in the spatio-temporal domain is one way for behavioral analysis of ego vehicle. A behavioral analysis step becomes extra important in uncertain situations to make safe decisions in trajectory planning (Hoel et al., 2020). Consider an overtaking example as shown in Figure 1.8.a), the ego vehicle can have multiple tactical maneuvers depending on the initial situation of the ego vehicle and the surrounding environment.

It is now interesting how to represent the decision if the vehicle should overtake before or after the vehicle in the opposing lane has passed. When the approaching obstacle in Figure 1.8(a) is too close to the obstacle in front of the ego vehicle, the blue surfaces representing the obstacle-free corridor illustrated in Figure 1.8(b) get closer and contact each other. In Figure 1.9, the region where two vehicles are close to each other form a hole, representing a collision region and therefore not feasible to pass.

Depending on the initial velocity of the ego and approaching vehicle, a tactical maneuver above the collision region and another maneuver below the collision region is possible and illustrated in Figure 1.10. Therefore, with the same cost function, a vehicle can make different maneuvers depending on the states of the ego vehicle and surrounding environment.

Figure 1.7: Distance-time graph of an ego vehicle with red and blue blocks as moving obstacles and calculated green trajectory for the ego vehicle.

1.5 Proposed Trajectory Planning Algorithms

To address the research objectives and planning problems, different trajectory planning algorithms are proposed. The proposed planning algorithms are designed to solve complex traffic scenarios such as roundabouts, intersections (Morsali, Åslund, et al., 2019), overtaking scenarios, and roads with aggressive curvatures, and this is especially interesting for heavy-duty vehicles that may roll over if lateral acceleration becomes too large.

A model predictive controller is designed for safe path and speed planning of a heavy-duty vehicle. Both speed and path planners are optimization based algorithms aiming at minimizing traveling time and distance, respectively. Additionally, the planner concentrates on identifying roll behavior of a truck in aggressive driving maneuvers.

In a proposed prioritized planning approach, a search based planner is used for path and speed planning of a non-holonomic vehicle. The study mainly investigate critical safety and comfort requirements on the vehicle and avoiding static and dynamic moving obstacles.

A major part of this thesis is dedicated to trajectory planning utilizing support vector machine (SVM) formulation. The SVM formulation is based on the insight attained from the road network, the position and temporal information of surrounding obstacles, and the mission defined for the ego ve-

Figure 1.8: a) A schema of the takeover scenario with blue vehicle as ego vehicle and green vehicles as obstacles. b) Test scenario with obstacles, calculated corridor and trajectory.

hicle. An obstacle-free corridor, a heuristic that accurately calculates remaining traveling, and a pruning technique to avoid unnecessary control inputs are main outcomes of the SVM solution.

Figure 1.9: Collision free corridor in a scenario with two moving obstacle and stationary obstacles on the road side. The hole is a representation of two surfaces interfered to each other in the overtaking example. The upper and lower part of the hole is collision free region.

Figure 1.10: Collision-free corridor for overtake scenario. The red and blue blocks represent the moving obstacles and the points in cyan represent a collision region.

1.6 Summary and Contributions of Included Papers

In this section, the type of problem to be solved, the solutions proposed and simulations conducted to show the properties of the proposed solutions in the included contributions are briefly explained. The thesis deals with trajectory planning of autonomous vehicles in traffic situations where three first papers are on the trajectory planning in spatio-temporal domain with a focus on collision avoidance and computational efficiency and the last two papers are decoupled trajectory planning with collision avoidance and respecting comfort and safety requirements.

Paper I

Mahdi Morsali, Erik Frisk and Jan Åslund “*Spatio-Temporal Planning in Multi-Vehicle Scenarios for Autonomous Vehicle Using Support.*” IEEE Transactions on Intelligent Vehicles, 2021.

The performance of planning algorithms is significantly dependent on the complexity of the road network and number of vehicles involved in planning. To address the planning complexity introduced in Section 1.2, a time efficient trajectory planner is proposed in a two step procedure where the first step is calculating an obstacle free corridor. An A* search is then used in a lattice, containing position, heading angle and velocity, for planning inside the obstacle free corridor.

The search space is efficiently characterized and a heuristic is derived by solving an optimization problem formulated as an SVM. The proposed heuristic contains information about road network and moving obstacles and accurately estimates the remaining traveling time to the destination which results in significant reduction of the trajectory planning time.

A roundabout scenario and two takeover scenarios with multiple moving obstacles are simulated to show the performance and generality property of the proposed search algorithm. A behavioral analysis, as introduced in Section 1.4, is conducted in a takeover scenario with a single cost function to show different tactical maneuvers the vehicle can take in different situations.

The obstacle data required for the SVM formulation is calculated by mapping the position and behavior of the obstacles to the spatio-temporal domain using estimated speed and acceleration of the obstacles. The SVM formulation, provides an obstacle-free corridor between obstacles labeled as left and

right. The labeling process for the obstacles is automated using the structure of the road network and the mission defined for the ego vehicle.

An important step in the proposed A* based trajectory planning, is calculation of kinematically feasible motion primitives. The primitives are calculated once and offline, by solving optimal control problems. A speed profile is assigned to the motion primitives in an online procedure during the search process. The speed profile, handles safety and comfort criteria as will be discussed in more detail in papers IV and V.

The SVM heuristic is combined with a pruning strategy to further decrease the computational load. The pruning strategy significantly reduces the number of required motion primitives during the A* search and the effects of pruning and the SVM heuristic are investigated by exploring the number of visited nodes. An optimal control trajectory planning is formulated and the results are compared to the results of A* search. In an overtaking scenario, while the greedy search does not find a solution after exploring 450,000 nodes, the proposed algorithm calculates a trajectory with 2,024 explored number of nodes. In another roundabout scenario, using the pruning algorithm and the SVM heuristic, an A* and a best-first algorithm calculate a trajectory with 14,491 and 51 explored nodes, respectively. On the other hand, in the same scenario an A* and best-first search increase the number of explored nodes from 18,581 to 91,581.

Paper II

Mahdi Morsali, Erik Frisk and Jan Åslund “*Geometrical Based Trajectory Calculation for Autonomous Vehicles in Traffic Scenarios.*” Submitted to Conference, 2021.

The main focus of this paper is to investigate the complexity and robustness issues mentioned in Section 1.2, respectively. A key observation from paper I is that the SVM solution provides an accurate estimation of remaining time in a mission for the autonomous vehicle. Additionally, the SVM surfaces contain information about obstacle regions and collision zones. The significant reduction in the number of explored nodes with the new heuristic, and smoothness property of the Gaussian kernel in SVM formulation, inspired trajectory planning solely with the geometry of the SVM surfaces. Robustness properties of the proposed method is investigated by randomly initiated scenarios and different numbers of obstacle vehicles.

In this paper, a novel trajectory planning is proposed for an autonomous vehicle in complex traffic scenarios and multiple vehicles as obstacles. The algorithm is a geometrical based planning approach, a planning approach without a need to search. The geometry required for planning is derived from a surface in spatio-temporal environment by solving a support vector machine formulation with a Gaussian kernel. The maximum separating surfaces has maximum distance from moving and stationary obstacles and passes through the start and destination position of the ego vehicle.

The trajectory is calculated by an integration on a surface, using the heading angle, extracted from maximum separating surface and acceleration, using the potential collision regions and avoiding accelerations leading to collision. The vehicle aims at driving as fast as possible while respecting safety and comfort criteria. In a second step, to ensure a kinematically feasible trajectory, a PID speed controller and a nonlinear state feedback controller to follow the generated path are utilized.

The properties of the calculated trajectory, specially the curvature, is inherited from the surface calculated by SVM formulation. The surface in the spatio-temporal domain with a smoothness property leads to the calculation of a smooth trajectory for the autonomous vehicle. Therefore, using the gradient of calculated surface with respect to space and time gives proper direction to move towards destination. The robustness of the algorithm is investigated through a large number of simulations in a roundabout scenario. The algorithm shows real time performance and kinematically feasible trajectories through a large number of traffic scenarios with multiple vehicles as obstacles.

Paper III

Mahdi Morsali, Jan Åslund and Erik Frisk “*Trajectory Planning for Autonomous Vehicles in Time Varying Environments Using Support Vector Machines.*” IEEE Intelligent Vehicles Symposium (IV), China, 2018.

Trajectory planning with obstacle avoidance has inherent complexity problems. This paper addresses this issue by first solving a convex optimization problem to characterize a search space that can be explored more efficiently. A novel trajectory planning is introduced by initially formulating the surrounding environment of the ego vehicle as obstacle-free and obstacle-existing. As a first step, the dynamic and static obstacles, using the estimated velocity and

acceleration, are mapped into time-space domain. Feasible time-monotonic trajectories for the obstacles are sought with time and space as states.

Representation of the surrounding environment in the time-space domain enables consideration of dynamic changes in the environment. The obstacles are then classified as left and right obstacles, according to the structure of the road and the ego vehicle's mission. Solving the convex optimization problem not only provides a characterization of the surrounding environment, but also an obstacle free surface is derived and used in a cost function formulation. For planning, a greedy search algorithm, conducted in the formulated obstacle-free environment, is used with traveling time as cost function. The deviation from the obstacle free surface is used in the cost function during planning search to penalize the deviated motion primitives. Representing the ego vehicle's surrounding environment with a single formula, $|f(w)| \leq 1$ with f as a smooth function and $w = (x, y, t)$ as spatio-temporal coordinates, results in reduced search space for the planning algorithm and the search is focused in the obstacle-free region.

The main contribution of this work is formulation of a reduced search space and trajectory planning in the search space. Using a non-holonomic kinematics with seven states in the planning search, including steer angle, velocity and acceleration, gives the flexibility to restrain the states to a comfort and safety zone. Since the primitives are calculated online, compared to a lattice based planner, the planner here, does not need to have discrete set of initial heading angle and position and the size of the primitives are flexible.

A static rollover criteria, considering the curvature of the calculated motion primitives, is used for safe speed planning. The steering rate and jerk, that are control inputs in the kinematic model, are limited to further satisfy comfort issues. The approach is possible to use in a model predictive controller over a finite receding horizon. The dimensions of the vehicle is considered in planning to ensure a collision free trajectory calculation in the obstacle-free zone. The results of the simulations, conducted in two takeover scenarios, represent that the proposed approach is collision free and the states are within the prescribed limits and satisfy the comfort and safety criteria.

Compared to planners introduced in Papers I and II, here a model with more states and therefore higher flexibility in restricting safety and comfort issues described in Section 1.2 is introduced. Although the planner is more flexible in restricting the physical model, the computational time is higher and

improvements, discussed as possible future work in Section 1.7, are required to make it more time efficient.

Paper IV

Mahdi Morsali, Erik Frisk and Jan Åslund “*Real-time velocity planning for heavy duty truck with obstacle avoidance.*” IEEE Intelligent Vehicles Symposium (IV), USA, 2017.

Here, the proposed algorithm deals with the calculation of a smooth path follower and a speed profile for a heavy duty vehicle, satisfying safety and comfort requirements discussed in Section 1.2. An important safety criterion for a heavy-duty vehicle, due to the high center of gravity, is rollover prevention. For real-time purposes, a minimum complexity roll dynamic model is identified using collected roll angle and lateral acceleration data from a heavy-duty truck. Two data sets, one with aggressive maneuvers and enough excitation for training, and the other for testing, are chosen for model estimation. A second order pendulum model and a first order model are used to identify the roll behavior of the truck.

A two step model predictive controller is then used to calculate the steer angle and velocity of the vehicle. In the first step, a least-squares method is used to minimize the distance between the vehicle position and the given path to follow. The second step calculates an optimal speed profile by minimizing the traveling time, considering a dynamic lateral load transfer criterion for rollover prevention, and also the constraints on steer rate, velocity and acceleration. A moving obstacle avoidance strategy is implemented by manipulating the final velocity of the vehicle in confrontation with an obstacle vehicle.

By comparing the first order model and the pendulum model, it is observed that the first order model is sufficient and as accurate as the second order pendulum model. The first order model reduces computational complexity and enables real time speed planning for the autonomous vehicle. Two test maneuvers are simulated with moving obstacles to show how the algorithm behaves in roads with large curvature and presence of moving obstacles. The calculated path and speed profiles indicate that the lateral load transfer is within the safe bounds defined for a heavy duty vehicle and the vehicle is able to smoothly follow the given coordinates.

Paper V

Mahdi Morsali, Erik Frisk and Jan Åslund “*Deterministic Trajectory Planning for Non-Holonomic Vehicles Including Road Conditions, Safety and Comfort Factors.*” IFAC Advanced Automotive Control Conference (IFAC-AAC), France, 2019.

This paper covers essential safety and comfort criteria and real time calculation discussed in Section 1.2. A decoupled search based speed planning with a focus on reduced roll model complexity is explored and the roll behavior of the vehicle is investigated in the planner by considering road banking and path curvature. Additionally, vehicle skidding that is directly influenced by friction and road banking is applied as a safety requirements on the speed profile.

To avoid abrupt changes in steering or jerky motions in the vehicle, comfort criteria are applied to the speed profile. For a given path, the steer rate has direct impact on the vehicle velocity and therefore, restricting the steer rate, a corresponding speed limit is calculated. The vehicle comfort in longitudinal direction is achieved by restraining the speed, acceleration and jerk limits.

To avoid collision, the surrounding moving obstacles are mapped into the distance-time graph of the ego vehicle and explored with an A* based search algorithm. Using a physical model enables restricting the safety and comfort requirements in the search algorithm. Comparing the results of optimal speed planning to the proposed search based speed planning shows a good agreement in the results.

Simulation scenarios with aggressive road banking and friction coefficients are conducted to ensure that skid and rollover constraints become active. The simulation results show the influence of banking on maximum rollover and skid limits. Indicated by the results, depending on the sign of the curvature, the road banking can increase or decrease both the rollover and skidding limits. The acceleration, jerk and speed limits are shown to be within the predefined limits and the speed profiles are observed to be smooth due to restrictions on the comfort criteria.

1.7 Conclusions and Future Work

Observing the results obtained from simulations and test scenarios, the objectives defined in the thesis are indicated to be satisfied. Physical models, enables planning for non-holonomic vehicles and at the same time restrict certain states of the vehicle to a comfort and safety zone. The constraints set for the comfort and safety requirements are shown to be within the pre-defined limits and significant improvement in computational time is achieved by integrating proposed heuristic and pruning technique to the search based algorithm. Integrating the proposed heuristic resulted from SVM solution the planning algorithm is shown to efficiently find trajectories in complex traffic scenarios, even when a best-first search algorithm is used. A dynamic roll model with reduced complexity is identified for a heavy duty vehicle that is able to represent vehicle behavior in aggressive driving maneuvers and reduce computational complexity. Vehicle and road characteristics impacts are investigated in calculation of a safe speed profile and indicated how banking and friction can relax or tighten the speed limits. The search based algorithms are compared to optimization based algorithms and the results are proven to be near optimal in path and speed planning algorithms conducted with A* search.

The intended direction and trajectory of moving obstacles are not known in traffic scenarios and the uncertainty should be considered while planning. This research question, can take at least two directions to either predict the behavior of obstacles with a learning based method or to map the uncertainty of moving obstacles in spatio-temporal domain of the ego vehicle.

In a coupled planning approach, there is only one cost function to explore, while in decoupled approaches investigated here, initially a shortest path is calculated in path planner and then a time optimal speed profile is calculated. The future research should also consider the differences between the optimal solutions obtained from a decoupled and coupled planning algorithms and possible losing of optimality when a decoupled approach is chosen.

The search network for the greedy search algorithm used in the obstacle-free corridor, gets increasingly large and the calculation time increases significantly. An upgrade of planning method to a hybrid-A* can help to reduce the computational complexity in spatio-temporal environment. A research question here is the improvements that can be made in computational time and possible loss of optimality through the change in the planning algorithm.

The objectives used for planning in this thesis is either shortest path or traveling time. A more reasonable cost function can consider the fuel consumption in planning approaches. The dynamics of the propulsion system and longitudinal dynamics could be integrated when planning to account for energy and fuel consumption, and this is especially relevant for heavy-duty vehicles. To avoid computational load with added degrees of freedom, motion primitives considering fuel efficiency can be calculated offline.

In the lattice based planner in paper I, the number of motion primitives were 9,476. A large number of motion primitives result in calculation of smooth speed profiles, it will however also increase the computational effort at the same time. A future work can optimize the number of motion primitives, by considering the primitives that are used most frequently. Further optimization can be achieved by considering the velocity and comfort criteria in choosing motion primitives, since most primitives are not usable in higher velocities.

The planning approaches proposed here are implemented in simulation scenarios, and the method weaknesses are not yet discovered. An implementation of the proposed planning method in a real vehicle would be instrumental help to understand the weak points and where to research improvements.

Bibliography

- Acheampong, Ransford A, Federico Cugurullo, Maxime Gueriau, and Ivana Dusparic (2021). “Can autonomous vehicles enable sustainable mobility in future cities? Insights and policy challenges from user preferences over different urban transport options.” In: *Cities* 112, p. 103134.
- Bagloee, Saeed Asadi, Madjid Tavana, Mohsen Asadi, and Tracey Oliver (2016). “Autonomous vehicles: challenges, opportunities, and future implications for transportation policies.” In: *Journal of modern transportation* 24.4, pp. 284–303.
- Bottasso, Carlo, Domenico Leonello, and Barbara Savini (2008). “Path planning for autonomous vehicles by trajectory smoothing using motion primitives.” In: *IEEE Transactions on Control Systems Technology* 16.6, pp. 1152–1168.
- Buehler, Martin, Karl Iagnemma, and Sanjiv Singh (2009). *The DARPA urban challenge: autonomous vehicles in city traffic*. Vol. 56. springer.
- Chu, K, J Kim, K Jo, and Myoungho Sunwoo (2015). “Real-time path planning of autonomous vehicles for unstructured road navigation.” In: *International Journal of Automotive Technology* 16.4, pp. 653–668.
- Den Berg, Jur van, Jack Snoeyink, Ming C Lin, and Dinesh Manocha (2009). “Centralized path planning for multiple robots: Optimal decoupling into sequential plans.” In: *Robotics: Science and systems*. Vol. 2. 2.5, pp. 2–3.

- Du, Xinxin, Kyaw Ko Ko Htet, and Kok Kiong Tan (2016). “Development of a genetic-algorithm-based nonlinear model predictive control scheme on velocity and steering of autonomous vehicles.” In: *IEEE Transactions on Industrial Electronics* 63.11, pp. 6970–6977.
- Elbanhawi, Mohamed, Milan Simic, and Reza Jazar (2015). “In the passenger seat: investigating ride comfort measures in autonomous cars.” In: *IEEE Intelligent transportation systems magazine* 7.3, pp. 4–17.
- Grymin, David J, Charles B Neas, and Mazen Farhood (2014). “A hierarchical approach for primitive-based motion planning and control of autonomous vehicles.” In: *Robotics and Autonomous Systems* 62.2, pp. 214–228.
- Guizhen, Yu, Li Honggang, Wang Pengcheng, Wu Xinkai, and Wang Yunpeng (2016). “Real-time bus rollover prediction algorithm with road bank angle estimation.” In: *Chaos, Solitons & Fractals* 89, pp. 270–283.
- Han, I-Chun, Bi-Cheng Luan, and Feng-Chi Hsieh (2014). “Development of autonomous emergency braking control system based on road friction.” In: *2014 IEEE International Conference on Automation Science and Engineering (CASE)*. IEEE, pp. 933–937.
- He, Defeng, Wentao He, and Xiulan Song (2020). “Efficient predictive cruise control of autonomous vehicles with improving ride comfort and safety.” In: *Measurement and control* 53.1-2, pp. 18–28.
- Hoel, Carl-Johan, Krister Wolff, and Leo Laine (2020). “Tactical decision-making in autonomous driving by reinforcement learning with uncertainty estimation.” In: *2020 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, pp. 1563–1569.
- Hu, Chuan, Zhenfeng Wang, Yechen Qin, Yanjun Huang, Jinxiang Wang, and Rongrong Wang (2019). “Lane keeping control of autonomous vehicles with prescribed performance considering the rollover prevention and input saturation.” In: *IEEE transactions on intelligent transportation systems* 21.7, pp. 3091–3103.
- ISO26262 (2018). *Road vehicles — Functional safety — Part 1: Vocabulary*. URL: <https://www.iso.org/standard/43464.html>.
- Khan, Junaid Ahmed, Lan Wang, Eddie Jacobs, Ahmedraza Talebian, Sabyasachee Mishra, Charles A Santo, Mihalis Golias, and Carmen Astorne-Figari (2019). “smart cities connected and autonomous vehicles readiness index.” In: *Proceedings of the 2nd ACM/EIGSCC Symposium on Smart Cities and Communities*, pp. 1–8.

- Kocić, Jelena, Nenad Jovičić, and Vujo Drndarević (2018). “Sensors and sensor fusion in autonomous vehicles.” In: *2018 26th Telecommunications Forum (TELFOR)*. IEEE, pp. 420–425.
- Kuderer, Markus, Shilpa Gulati, and Wolfram Burgard (2015). “Learning driving styles for autonomous vehicles from demonstration.” In: *2015 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, pp. 2641–2646.
- LaValle, Steven M (2006). *Planning algorithms*. Cambridge university press.
- Li, Bai, Youmin Zhang, Yuming Ge, Zhijiang Shao, and Pu Li (2017). “Optimal control-based online motion planning for cooperative lane changes of connected and automated vehicles.” In: *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, pp. 3689–3694.
- Li, Boyuan, Haiping Du, Weihua Li, and Bangji Zhang (2018). “Dynamically integrated spatiotemporal-based trajectory planning and control for autonomous vehicles.” In: *IET Intelligent Transport Systems* 12.10, pp. 1271–1282.
- Likhachev, Maxim and Dave Ferguson (2009). “Planning long dynamically feasible maneuvers for autonomous vehicles.” In: *The International Journal of Robotics Research* 28.8, pp. 933–945.
- Lim, Hazel Si Min and Araz Taeihagh (2018). “Autonomous vehicles for smart and sustainable cities: An in-depth exploration of privacy and cybersecurity implications.” In: *Energies* 11.5, p. 1062.
- Low, Chang Boon and Danwei Wang (2008). “GPS-based tracking control for a car-like wheeled mobile robot with skidding and slipping.” In: *IEEE/ASME transactions on mechatronics* 13.4, pp. 480–484.
- Lu, Ning, Nan Cheng, Ning Zhang, Xuemin Shen, and Jon W Mark (2014). “Connected vehicles: Solutions and challenges.” In: *IEEE internet of things journal* 1.4, pp. 289–299.
- Luders, Brandon, Mangal Kothari, and Jonathan How (2010). “Chance constrained RRT for probabilistic robustness to environmental uncertainty.” In: *AIAA guidance, navigation, and control conference*, p. 8160.
- Martínez-Díaz, Margarita and Francesc Soriguera (2018). “Autonomous vehicles: theoretical and practical challenges.” In: *Transportation Research Procedia* 33, pp. 275–282.

- Mersky, Avi Chaim and Constantine Samaras (2016). “Fuel economy testing of autonomous vehicles.” In: *Transportation Research Part C: Emerging Technologies* 65, pp. 31–48.
- Morsali, Mahdi, Jan Åslund, and Erik Frisk (2018). “Trajectory Planning for Autonomous Vehicles in Time Varying Environments Using Support Vector Machines.” In: *IEEE intelligent vehicles symposium*.
- (2019). “Trajectory Planning in Traffic Scenarios Using Support Vector Machines.” In: *IFAC-PapersOnLine* 52.5, pp. 91–96.
- Morsali, Mahdi, Erik Frisk, and Jan Åslund (2017). “Real-time velocity planning for heavy duty truck with obstacle avoidance.” In: *IEEE intelligent vehicles symposium*.
- (2019). “Deterministic Trajectory Planning for Non-Holonomic Vehicles Including Road Conditions, Safety and Comfort Factors.” In: *IFAC advanced automotive control conference*.
- (2020). “Spatio-Temporal Planning in Multi-Vehicle Scenarios for Autonomous Vehicle Using Support Vector Machines.” In: *IEEE transactions on intelligent vehicles*.
- (2021). “Geometrical Based Trajectory Calculation for Autonomous Vehicles in Traffic Scenarios.” In: *Submitted to Conference*.
- Paden, Brian, Michal Čáp, Sze Zheng Yong, Dmitry Yershov, and Emilio Frazzoli (2016). “A survey of motion planning and control techniques for self-driving urban vehicles.” In: *IEEE Transactions on intelligent vehicles* 1.1, pp. 33–55.
- Pettigrew, Simone, Zenobia Talati, and Richard Norman (2018). “The health benefits of autonomous vehicles: public awareness and receptivity in Australia.” In: *Australian and New Zealand journal of public health* 42.5, pp. 480–483.
- Pham, Quang-Cuong (2015). “Trajectory Planning.” In: *Handbook of Manufacturing Engineering and Technology*. Ed. by Andrew Y. C. Nee. London: Springer London, pp. 1873–1887. ISBN: 978-1-4471-4670-4.
- Shim, Taehyun and Chinar Ghike (2007). “Understanding the limitations of different vehicle models for roll dynamics studies.” In: *Vehicle system dynamics* 45.3, pp. 191–216.
- Singh, Santokh (2015). *Critical reasons for crashes investigated in the national motor vehicle crash causation survey*. Tech. rep.
- Stern, Raphael E, Yuche Chen, Miles Churchill, Fangyu Wu, Maria Laura Delle Monache, Benedetto Piccoli, Benjamin Seibold, Jonathan Sprinkle,

- and Daniel B Work (2019). “Quantifying air quality benefits resulting from few autonomous vehicles stabilizing traffic.” In: *Transportation Research Part D: Transport and Environment* 67, pp. 351–365.
- Taeihagh, Araz and Hazel Si Min Lim (2019). “Governing autonomous vehicles: emerging responses for safety, liability, privacy, cybersecurity, and industry risks.” In: *Transport reviews* 39.1, pp. 103–128.
- Woldeamanuel, Mintesnot and Dang Nguyen (2018). “Perceived benefits and concerns of autonomous vehicles: An exploratory study of millennials’ sentiments of an emerging market.” In: *Research in Transportation Economics* 71, pp. 44–53.
- Yoo, Jehong and Reza Langari (2018). “A predictive perception model and control strategy for collision-free autonomous driving.” In: *IEEE Transactions on Intelligent Transportation Systems* 20.11, pp. 4078–4091.
- Zhou, Hongliang, Jinwu Gao, and Haifeng Liu (2020). “Vehicle speed preview control with road curvature information for safety and comfort promotion.” In: *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, p. 0954407020972851.
- Zhu, Sheng and Bilin Aksun-Guvenc (2020). “Trajectory Planning of Autonomous Vehicles Based on Parameterized Control Optimization in Dynamic on-Road Environments.” In: *Journal of Intelligent & Robotic Systems* 100.3, pp. 1055–1067.
- Ziegler, Julius and Christoph Stiller (2009). “Spatiotemporal state lattices for fast trajectory planning in dynamic on-road driving scenarios.” In: *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, pp. 1879–1884.

Papers

The papers associated with this thesis have been removed for copyright reasons. For more details about these see:

<http://urn.kb.se/resolve?urn=urn:nbn:se:liu:diva-173940>

Dissertations
Division of Vehicular Systems
Department of Electrical Engineering
Linköping University

- No. 1 Magnus Pettersson, *Driveline Modeling and Control*, 1997.
- No. 2 Lars Eriksson, *Spark Advance Modeling and Control*, 1999.
- No. 3 Mattias Nyberg, *Model Based Fault Diagnosis: Methods, Theory, and Automotive Engine Applications*, 1999.
- No. 4 Erik Frisk, *Residual Generation for Fault Diagnosis*, 2001.
- No. 5 Per Andersson, *Air Charge Estimation in Turbocharged Spark Ignition Engines*, 2005.
- No. 6 Mattias Krysander, *Design and Analysis of Diagnosis Systems Using Structural Methods*, 2006.
- No. 7 Jonas Biteus, *Fault Isolation in Distributed Embedded Systems*, 2007.
- No. 8 Ylva Nilsson, *Modelling for Fuel Optimal Control of a Variable Compression Engine*, 2007.
- No. 9 Markus Klein, *Single-Zone Cylinder Pressure Modeling and Estimation for Heat Release Analysis of SI Engines*, 2007.
- No. 10 Anders Fröberg, *Efficient Simulation and Optimal Control for Vehicle Propulsion*, 2008.
- No. 11 Per Öberg, *A DAE Formulation for Multi-Zone Thermodynamic Models and its Application to CVCP Engines*, 2009.
- No. 12 Johan Wahlström, *Control of EGR and VGT for Emission Control and Pumping Work Minimization in Diesel Engines*, 2009.
- No. 13 Anna Pernestål, *Probabilistic Fault Diagnosis with Automotive Applications*, 2009.
- No. 14 Erik Hellström, *Look-ahead Control of Heavy Vehicles*, 2010.
- No. 15 Erik Höckerdal, *Model Error Compensation in ODE and DAE Estimators with Automotive Engine Applications*, 2011.

- No. 16** Carl Svärd, *Methods for Automated Design of Fault Detection and Isolation Systems with Automotive Applications*, 2012.
- No. 17** Oskar Leufvén, *Modeling for Control of Centrifugal Compressors*, 2013.
- No. 18** Christofer Sundström, *Model Based Vehicle Level Diagnosis for Hybrid Electric Vehicles*, 2014.
- No. 19** Andreas Thomasson, *Modeling and control of actuators and co-surge in turbocharged engines*, 2014.
- No. 20** Emil Larsson, *Model Based Diagnosis and Supervision of Industrial Gas Turbines*, 2014.
- No. 21** Andreas Myklebust, *Dry Clutch Modeling, Estimation, and Control*, 2014.
- No. 22** Tomas Nilsson, *Optimal Engine Operation in a Multi-Mode CVT Wheel Loader*, 2015.
- No. 23** Daniel Jung, *Diagnosability Performance Analysis of Models and Fault Detectors*, 2015.
- No. 24** Martin Sivertsson, *Optimal Control of Electrified Powertrains*, 2015.
- No. 25** Peter Nyberg, *Evaluation, Generation, and Transformation of Driving Cycles*, 2015.
- No. 26** Kristoffer Lundahl, *Models and Critical Maneuvers for Road Vehicles*, 2016.
- No. 27** Vaheed Nezhadali, *Modeling and Optimal Control of Heavy-duty Powertrains*, 2016.
- No. 28** Xavier Llamas, *Modeling and Control of EGR on Marine Two-Stroke Diesel Engines*, 2018.
- No. 29** Sergii Voronov, *Machine Learning for Predictive Maintenance*, 2020.
- No. 30** Victor Fors, *Autonomous Vehicle Maneuvering at the Limit of friction*, 2020.
- No. 31** Fatemeh Mohseni, *Decentralized Optimal Control for Multiple Autonomous Vehicles in Traffic Scenarios*, 2021.

FACULTY OF SCIENCE AND ENGINEERING

Linköping Studies in Science and Technology, Dissertation No. 2126, 2021
Department of Electrical Engineering

Linköping University
SE-581 83 Linköping, Sweden

www.liu.se