

Implementation and Evaluation of Stanley-Based Path-Following Controllers for Autonomous Vehicles with Conventional Steering

Scientific work for obtaining the academic degree
Bachelor of Science (B.Sc.)
at the TUM School of Computation, Information and Technology.

Supervisor	Prof. Dr.-Ing. Hans-Georg Herzog Chair of Energy Conversion Technology
Advisor	Johannes Rein M.Sc. Dr.-Ing. Jonathan Brembeck DLR - Institute of System Dynamics and Control (SR)
Submitted by	Vincent Sperr Mönchbergstraße 29 81825 München +49 157 80883146
Submitted on	06.04.2026

Implementierung und Evaluierung einer Pfadfolgeregelung für autonome Fahrzeuge mit konventioneller Lenkung



Allgemeine Problemstellung:

Das Team Fahrzeugsystemdynamik und Regelungstechnik des Instituts für Fahrzeugkonzepte ertüchtigt aktuell ein neues Versuchsfahrzeug im Maßstab 1:8. Entwicklungsziel ist es autonom einen vorgegebenen Pfad abfahren zu können um damit in einer komplexen Infrastruktur wie dem Gelände DLR in Oberpfaffenhofen fahren zu können.

Das Versuchsfahrzeug ist mit einer Vielzahl an Sensoren wie einer GNSS, optischen Kameras, einem Lidar sowie mehreren IMUs (Inertial Measurement Units) ausgestattet. Mit Hilfe deren Messdaten soll ein Pfadfolgeregler (PFC), den zu stellenden Lenkwinkel und das Motordrehmoment bestimmt, sodass ein vorgegebener Pfad möglichst genau abgefahren wird. Herausforderungen sind dabei u.a. die Trägheit des Antriebstrangs, Nichtlinearitäten im Reifen-Straße-Kontakt sowie Latenzen der Sensorik.

Aktuell wird eine Abwandlung des [geoPFC](#) Algorithmus genutzt, der ursprünglich für überaktuierte Fahrzeuge wie dem DLR ROboMObil (unabhängige Lenkung der Räder) entwickelt wurde. Da das neue Fahrzeug eine reine Vorderachslenkung hat, liegt die Annahme nahe, dass alternative PFC-Algorithmen, wie der [Stanley Path-Tracking Controller](#), für die gegebene Fahrzeugarchitektur besser geeignet sind. Diese sollen systematisch innerhalb der Bachelorarbeit implementiert und an Hand von vordefinierten Szenarien im Vergleich zu dem geoPFC-Algorithmus bewertet werden.

Aufgabenstellung:

- Literaturrecherche zu etablierten PFC-Algorithmen
- Implementierung des „Stanley Path-Tracking Controllers“
- Simulative Untersuchung dessen anhand eines bestehenden Fahrzeugmodells
- Optional: Inbetriebnahme des PFC-Algorithmus auf dem Versuchsfahrzeug

Zielsetzung

- Literaturrecherche zu PFC-Algorithmen
- Simulative Evaluierung des „Stanley Path-Tracking Controllers“ im Vergleich zur geoPFC hinsichtlich Regelgüte und Stabilität bei reduzierten Abtastraten
- Optional: Evaluierung des „Stanley Path-Tracking Controllers“ am Versuchsfahrzeug

Voraussetzungen:

- Gute Kenntnisse der Regelungstechnik
- Kenntnisse in Matlab/Simulink, Python, Modelica

Betreuer beim DLR:

Johannes Rein, Dr. Jonathan Brembeck

Möglicher Beginn:

15.12.2025.

Bewerbungen an:

johannes.rein@dlr.de

Abstract

The miniAFM is an autonomous test vehicle on a 1:8 scale at DLR. The current path-following controller, the geoPFC, was originally developed for an over-actuated vehicle with four independently steerable wheels. However, the miniAFM has conventional front-axle steering. This work implements three Stanley-based controllers and evaluates them against the geoPFC. The variants include the base Stanley, a predictive Stanley with a prediction horizon, and an enhanced Stanley with feedforward control via a kinematic reference model.

Simulation tests across three scenarios show that the Predictive Stanley achieves the lowest lateral RMSE, followed by the base Stanley. Robustness tests with increased latency show the base Stanley to be the most robust choice without retuning, whilst the Predictive Stanley performs best after parameter tuning. On the real vehicle, the base Stanley outperforms the geoPFC in terms of lateral RMSE. The results confirm the Stanley-based controllers as promising alternatives to the geoPFC on the miniAFM. The enhanced Stanley requires a more detailed comparison by using a parameter optimization.

Zusammenfassung

Das miniAFM ist ein autonomes Testfahrzeug im Maßstab 1:8 am DLR. Der aktuelle Pfadfolgeregler, der geoPFC, wurde ursprünglich für ein überaktuiertes Fahrzeug mit vier unabhängig lenkbaren Rädern entwickelt. Das miniAFM hat jedoch eine konventionelle Vorderachslenkung. Diese Arbeit implementiert drei Stanley-basierte Regler und bewertet sie gegenüber dem geoPFC. Als Varianten gibt es den Basis-Stanley einen Prädiktiven Stanley mit Vorhersagehorizont und einen enhanced Stanley mit Vorsteuerung über ein kinematisches Referenzmodell.

Simulationstests bei $3 \frac{m}{s}$ über drei Szenarien zeigen, dass der Prädiktive Stanley den niedrigsten lateralen RMSE erreicht, gefolgt vom Basis-Stanley. Robustheitstests mit erhöhter Latenz zeigen den Basis-Stanley als robusteste Wahl ohne Nachstimmung, während der Prädiktive Stanley nach Parameteranpassung am besten abschneidet. Am realen Fahrzeug unterbietet der Basis-Stanley den geoPFC vom lateralen RMSE. Die Ergebnisse bestätigen die Stanley-basierten Regler als vielversprechende Alternativen zum geoPFC auf dem miniAFM. Der enhanced Stanley muss mittels Parameter Optimierung noch genauer verglichen werden.

Table of Contents

Abstract.....	3
Zusammenfassung	3
Table of Contents	5
Nomenclature	7
List of Figures.....	11
List of Tables	12
1. Introduction.....	13
1.1 Motivation.....	13
1.2 Goal of this Thesis	14
1.3 Path Following Control.....	14
2. The miniAFM.....	17
2.1 Test Vehicle	17
2.1.1 Sensor Technology	17
2.1.2 Simulation model.....	19
2.2 Current path following controller of the miniAFM	21
2.2.1 Time Independent Path Interpolation	22
2.2.2 Control Algorithm.....	24
3. Stanley-based path following control.....	28
3.1 Front Axle TIPI.....	28
3.2 Stanley Controller	29
3.3 Predictive Stanley Controller.....	32
3.4 Reference Model for the enhanced Stanley controller.....	34
3.5 Enhanced Stanley Controller	36
3.5.1 Reformulated Stanley Law	36
3.5.2 Enhanced Stanley Law.....	37
4. Simulative Evaluation.....	39
4.1 Evaluation Criteria.....	39
4.2 Test Scenario U Turn	40
4.3 Test scenario double bend.....	41
4.4 Test on Race Track	43
4.5 Robustness Tests.....	45
4.5.1 Robustness to initial Offset.....	45

4.5.2	Robustness to system delay	46
4.6	Evaluation.....	51
5.	Evaluation on the test vehicle.....	54
5.1	Results	54
5.2	Evaluation.....	56
6.	Conclusion.....	57
	References	59
	Danksagung.....	62
A.	Appendix	63
A.1.	Simulation Model Parameter.....	63
A.2.	Parameters for Testing scenarios.....	63
A.3.	Improved Parameters.....	66

Nomenclature

Mathematical Expressions

$\ \cdot\ $	Euclidian norm of matrix or vector
$\operatorname{argmin} f(\boldsymbol{x})$	argument $\boldsymbol{x}$ of cost function $f(\boldsymbol{x})$ yielding the minimum
$\arctan(\cdot)$	Inverse tangent function
$\frac{d}{ds}$	Partial derivative with respect to arc length
$\frac{d}{dt}$	Time derivative

Abbreviations

AFM	AI for Mobility
CAN	Controller Area Network
CoG	Center of Gravity
DARPA	Defense Advanced Research Projects Agency
DLR	German Aerospace Center
FMI	Functional Mock-up Interface
FMU	Functional Mock-up Unit
GCA	Geometric Control Allocation
geoPFC	Geometric Path Following Controller
GLIM	GPU-Accelerated LiDAR-Inertial Mapping
GPS	Global Positioning System
ICR	Instantaneous Center of Rotation
LiDAR	Light Detection and Ranging
LQR	Linear Quadratic Regulator
MPC	Model Predictive Control
PID	Proportional-Integral-Derivative
RMSE	Root Mean Square Error
ROboMObil / ROMO	Robotic Electric Vehicle of DLR
RTK	Real-Time Kinematic
SLAM	Simultaneous Localisation and Mapping
TIPI	Time Independent Path Interpolation
VESC	Vedder Electronic Speed Controller

Symbols

C	Tire cornering stiffness
e_{lat}	Lateral error
$e_{lat,f}$	Lateral error at front axle

e_x^P	Tangential error in path frame
F_N	Normal force at tire contact patch
F_{Total}	Total friction force at tire contact
F_x^W, F_y^W	Longitudinal and lateral tire force in wheel frame
i_g	Powertrain gear ratio
i_s	Steering ratio
J_ψ	Yaw moment of inertia
K	Stanley cross-track gain
$k_{d,steer}$	Steering actuator damping gain
$K_{d,yaw}$	Yaw rate damping gain
K_k	Weighting factor for prediction step k
K_P	TIPI dynamic root-finding gain
K_{prot}	Low-speed protection gain
l	Wheelbase
L	Wheelbase
l_d	Look-ahead distance
l_f	Distance from CoG to front axle
l_r	Distance from CoG to rear axle
m	Vehicle mass
M_i	Yaw moment from wheel i
n	Number of simulation samples
N	Number of prediction steps
$\mathbf{p}_c$	Vehicle position
$\mathbf{p}_f$	Front axle centre position
$\mathbf{p}_{P(s)}$	Path position as function of arc length
$\mathbf{p}_r$	Rear axle centre position
$P_{ref,ff}$	Front axle reference point
$P_{ref,ff}$	Feedforward reference point
$P_{ref,r}$	Rear axle reference point
q	Vehicle path arc length
r	Wheel radius
r_c	Radius from turning centre to vehicle position
r_p	Radius from turning centre to path reference point
$r_{r,ref}$	Curve radius at rear axle reference
s	Arc length parameter along the reference path
s^*	Optimal arc length parameter
$\dot{s}$	Time derivative of arc length parameter

s_{ff}	Feedforward arc length offset
t_{ff}	Feedforward time
T_{pred}	Prediction horizon length
u	Input vector of the vehicle model
v	Absolute vehicle speed
$v_{p(s)}$	Reference velocity along path tangent
v_{slip}	Combined slip velocity magnitude
$v_{slip,x}, v_{slip,y}$	Longitudinal and lateral slip velocity
v_x^C, v_y^C	Longitudinal and lateral velocity in car frame
v_x^G	Tangential velocity component in global frame
x	State vector of the vehicle model
x^G, y^G	Vehicle position in the global frame
α	Angle between vehicle heading and look-ahead line
β	Vehicle sideslip angle
β^*	Demanded vehicle sideslip angle
δ	Steering angle
δ_{add}	Combined additional steering correction
δ_{calc}	Calculated steering angle before saturation
δ_{demand}	Demanded steering angle
$\delta_{Enhanced}$	Output steering angle of the Enhanced Stanley controller
δ_k	Stanley steering angle at prediction step k
δ_{max}	maximum achievable steering angle
δ_{ref}	Kinematic reference steering angle
$\delta_{ref,ff}$	Feedforward reference steering angle
δ_{steer}	Steering actuator damping correction
Δt	Prediction time step size
δ_{yaw}	Yaw rate damping steering correction
$\Delta\psi$	Heading error corrected for steady-state slip
κ	Path curvature
κ_{ref}	Path curvature at rear axle reference point
$\kappa_{ref,ff}$	Path curvature at feedforward point
λ_e	Path constant for lateral error dynamics
$\lambda(s)$	Motion demand vector as function of arc length
λ_ψ	Path constant for heading error dynamics
μ	Friction coefficient
ρ_{ICR}	ICR curvature
ρ_{ICR}^*	Demanded ICR curvature

τ_{demand}		Demanded torque
τ_x		Time constant for error dynamics
ψ		Heading error
ψ_f		Heading error at front axle
$\dot{\psi}_{path}$		Expected yaw rate from path curvature
ψ_{path}		Path tangent angle at reference point
$\psi_{path,r}$		Path tangent angle at rear axle reference point
$\psi_{ref,f}$		Path direction of movement at front axle
ψ_{ss}		Steady-state sideslip angle at front axle
$\psi_{ss,r}$		Steady-state sideslip angle at rear axle
$\dot{\psi}_{veh}$		Vehicle yaw rate
ψ_{veh}		Vehicle yaw angle
ω_i		Angular velocity of wheel i

List of Figures

Figure 2.1: MiniAFM with sensor technology	18
Figure 2.2: Mapping of the Planar Movement on the miniAFM.....	19
Figure 2.3: Dynamic Root finding process. Starting from the initial guess s_0 converging to s^*	22
Figure 2.4: .Display of the radii r_p , r_c and its relations.	23
Figure 3.1: Geometric Visualization of the Stanley Controller.	29
Figure 3.2: Visualization of the predictive Stanley controller. The current vehicle state is shown in black, while the predicted future states are depicted in grey. The green steering angle δ represents the final steering angle derived from the weighted prediction horizon.....	33
Figure 3.3: The rear axle center of the reference model on the path with tangential orientation $\psi_{path,r}$. Due to the rear axle slip angle $\psi_{ss,r}$, the vehicle orientation deviates from the path tangent. The front axle center $P_{ref,f}$ results from the wheelbase l , the path tangent $\psi_{path,r}$, and the slip angle $\psi_{ss,r}$	35
Figure 3.4: Reference vehicle position and orientation. With the instant center of rotation, the curve radius $r_{r,ref}$ and the auxiliary variable h	36
Figure 3.5: Geometry of the Enhanced Stanley controller. The feedforward point $P_{ref,ff}$ is offset from $P_{ref,r}$ by the arc length s_{ff} in the direction of travel, resulting in the feedforward steering angle $\delta_{ref,ff}$	38
Figure 4.1: Trajectories of the controller on the simulative U-turn test, with extra zoom on the exit of the curve.....	40
Figure 4.2: Trajectories on the simulative double bend test with zoom in on the second arc towards the end straight.	42
Figure 4.3: Trajectories of the controller on the simulative racetrack.....	44
Figure 4.4: Trajectories of the controller compensating the offset.....	45
Figure 4.5: Improved trajectories of the controller compensating the offset.....	46
Figure 4.6: Trajectories of the controller with a latency of $100ms$	47
Figure 4.7: Improved trajectories with $100ms$ system delay.	48
Figure 4.8: Trajectories of the controller with a latency of $150ms$	49
Figure 4.9: Improved trajectories with $150ms$ delay	50
Figure 5.1: Controller trajectories on the race track with High Parameter set.	55
Figure 5.2: Controller Trajectories on the Race Track with Improved Parameter Set ...	55

List of Tables

Table 2.1.1: Vehicle Components	17
Table 2.1.2: Sensors with its Clock Rates on the miniAFM	19
Table 3.1: Reference Points of the Implemented Path Following Controllers.....	28
Table 4.2.1: Error Values on the U-turn.....	41
Table 4.3.1: Error Values on the double bend curve.....	43
Table 4.4.1: Error values on the racetrack.	44
Table 4.5.1: Error values with a Delay of 100ms.....	47
Table 4.5.2: Improved error values with 100ms delay.	48
Table 4.5.3: Error values with 150 ms delay.....	49
Table 4.5.4: Improved error values with 150 ms delay.	50
Table 4.6.1: Lateral RMSE across the test scenarios with 3 ms.....	51
Table 4.6.2: The improved lateral RMSE across each delay latency.....	52
Table 5.1.1: Error quantities for the evalauation on the vehicle with strong parameters	54
Table 5.1.2:Error quantities for the evaluation on the vehicle with adapted Parameters	56
Table A.1.1: Simulation Model Parameters for the miniAFM	63
Table A.2.1: List of the Control Parameter Set for the U-Turn Scenario	64
Table A.2.2: List of the Control Parameter Set for the Double Bend Curve	64
Table A.2.3: List of the Control Parameter Set for the race track.....	65
Table A.2.4: List of the Control Parameter Set for the Test on the miniAFM	65
Table A.3.1: List of the Control Parameter set for the offset.....	66
Table A.3.2: Parameter set used to improve tracking performance at 100ms delay.	67
Table A.3.3: Improved Parameter Set for 150 ms delay	67

1. Introduction

Autonomous vehicles have gained significant interest over the past decades, promising to change the view on future mobility and transportation. In the literature, autonomous driving is usually described as a system task that combines environment perception, decision making, motion planning, and vehicle control to perform the driving task with limited or no human intervention [Bad19]

The Society of Automotive Engineers classifies vehicle automation into six levels, from no automation at Level 0 to full automation at Level 5 where no human input is needed [Pen21]. Independent of the automation level, autonomous vehicles require reliable interaction between sensing, planning, and control to achieve safe and stable driving behaviour. One key component of the autonomous vehicle is the path following control. It is the task of ensuring the vehicle follows the desired path accurately. This control problem is independent of vehicle size. Research on scaled vehicles can also provide valuable information for larger systems. Thus, they are used extensively in academia and industry to develop and test autonomous driving algorithms before deploying them on full sized cars [Oke20]. The smaller size makes experiments cheaper and safer but the fundamental control problems remain the same. This thesis addresses one of those problems. Choosing and implementing the right path following controller for a 1:8 scale autonomous vehicle.

1.1 Motivation

The Vehicle System Dynamics and Control team at DLR's Institute of Vehicle Concepts is currently developing the miniAFM, a test vehicle for autonomous driving research. The long-term goal is to have the vehicle navigate on predefined paths through complex infrastructure like the DLR campus in Oberpfaffenhofen.

The path following controller currently running on the miniAFM is referred to as the geoPFC. Originally developed for the DLR ROboMObil, an over actuated vehicle with four independently steered and driven wheels [Rit16]. It uses a geometric control allocation that maps virtual motion demands to individual wheel steering angles using the Ackermann conditions. For the miniAFM, a simplified version is used which is limited to front wheel steering only. A central assumption in this allocation is zero lateral slip at the wheels. However, the miniAFM has a conventional front axle steering. This is a fundamentally different architecture than what the geoPFC was built for, although it is the current controller on the miniAFM.

1.2 Goal of this Thesis

The goal of this thesis is to implement Stanley-based path following controllers and evaluate whether they are better suited for the miniAFM than the existing geoPFC. They are evaluated against the geoPFC, across multiple test scenarios and different system delays. The comparison uses the lateral error and heading error as performance metrics. Lateral tracking performance is evaluated across three simulation scenarios while the robustness is assessed against an initial position offset and increased system latency. Finally, the controllers are also tested on the real vehicle.

The thesis is structured as follows. Chapter 2 describes the test vehicle, its sensors, the simulation model and the existing geoPFC controller. Chapter 3 presents the three Stanley-based controllers with their mathematical derivations and the necessary adaptations to the path interpolation. Chapter 4 contains the simulative evaluation across the test scenarios and the robustness tests. Chapter 5 presents the results from the real vehicle test, while chapter 6 concludes the thesis and gives an outlook on future work.

1.3 Path Following Control

Path following control is one of the key components in the autonomous vehicle pipeline [Pad16]. It is the part of vehicle motion control that guides a vehicle along a predefined path trying to minimize the deviation between the vehicle and the desired path. A major challenge of path following control is that real vehicles do not behave ideally. Sensor processing, communication, actuator dynamics, modelling errors, and tire slip can all reduce tracking performance. For this reason, path following controllers must not only achieve small tracking errors, but also remain robust under disturbances, delay, and changing operating conditions. Path following control can be grouped into three categories. The geometric, kinematic and dynamic model based [Keb23]. Each having different trade-offs in matter of simplicity and performance [Ame17]. The right choice depends on the speed range, available computation and vehicle operating limits.

Geometric Controllers

Geometric controllers compute the steering angle δ depending on geometric relationships between the vehicle and the path, without a vehicle model. Thus, only trigonometry is needed for the computation. The category has two renowned controllers.

The first one is the Pure Pursuit [Cou92]. It chooses a reference point on the path at a look ahead distance l_d and calculates the steering angle to drive onto a circular arc towards it. Its control law is formed as

$$\delta = \arctan\left(\frac{2L \cdot \sin(\alpha)}{l_d}\right) \quad (1.1)$$

Here L is the wheelbase and α the angle between the vehicle heading and the straight to the reference point. The look ahead distance is usually set proportional to the vehicle speed, with larger values the tracking is smoother, while shorter values increase the accuracy but increasing the risk of oscillation [Sni09]. The second one is the Stanley controller, which is part of this thesis and has a detailed description in chapter 3.

Kinematic Controllers

Kinematic controllers use models that assume no vehicle dynamics. Often used is the one lane bicycle model.

$$\dot{x} = v \cdot \cos(\psi_{\text{veh}}) \quad (1.2)$$

$$\dot{y} = v \cdot \sin(\psi_{\text{veh}}) \quad (1.3)$$

$$\dot{\psi}_{\text{veh}} = v \cdot \tan\left(\frac{\delta}{L}\right) \quad (1.4)$$

Here x and y are the rear axle position in the global frame, ψ_{veh} the vehicle heading angle, v the longitudinal velocity. The model is nonlinear but computationally cheap. It stays valid as long as lateral acceleration remains below roughly half the friction limit [Pol17]. It can be used with different control strategies. The range goes from simple PID controllers, applied directly to the error dynamics, to more advanced model-based approaches such as the linear-quadratic regulator (LQR) and model predictive control (MPC). LQR controllers linearize the model around the reference path and compute an optimal state-feedback gain and MPC discretizes the model, predicts the system state over a horizon, and optimizes the steering input under constraints.

Dynamic Controllers

At higher speeds or on slippery surfaces the no-slip assumption breaks down. Dynamic controllers add tire forces to the vehicle model. Instead of pure geometry, the equations describe the lateral and yaw dynamics through force and moment balances that depend on tire slip angles and cornering stiffness. The dynamic simulation model used throughout this thesis is described in detail in Chapter 2.1.2.

The same control strategies apply here as for the kinematic controllers. On top of that the dynamic model enables approaches like sliding mode control and H-infinity control that exploit the force-based structure for robustness against parameter uncertainty [Keb23]. Falcone et al. [Fal07] demonstrated dynamic MPC approaches on icy roads. These types

of controllers deliver the best tracking but for the model based approaches accurate tire parameters are needed.

Stanley based controller

The miniAFM currently operates at up to 2 m/s on the real vehicle. The goal is to drive significantly faster in the future. For the current speed range, a geometric controller is the practical choice. The Stanley controller falls into this category. It computes the steering angle from the geometric error between the vehicle and the path without requiring a detailed vehicle model. Its structure is simple and straightforward to implement (cf. Chapter 3). At the same time, it serves as a solid base for extensions that address more demanding conditions.

This thesis implements three Stanley-based variants. The Base Stanley uses the geometric control law directly. The Predictive Stanley extends it with a vehicle model that anticipates future states over a prediction horizon, drawing on the same forward-looking principle that has made model-predictive approaches one of the most widely studied methods in recent path tracking research [Sta23]. The enhanced Stanley adds a kinematic reference model and a feedforward term to compensate for system delay. All three build on the same geometric foundation but push it toward handling dynamic driving situations without the full complexity of model-based control. The detailed derivations are presented in Chapter 3.

2. The miniAFM

This chapter introduces the test vehicle used for path following control experiments at DLR FK-FSR. Section 2.1 presents the vehicle platform along with its sensor configuration, followed by the corresponding simulation model. Section 2.2 explains the currently implemented path-following controller, which serves as the baseline against which the newly implemented controllers in this thesis are compared.

2.1 Test Vehicle

For the testing vehicle the RC MXcarkit from MdynamiX, on a scale of 1:8, is used. The vehicle is suited for experimental testing of autonomous driving controllers. The vehicle is based on the Inferno GT chassis with an electric Kyosho Speed House Torx 8+ motor providing all-wheel drive. An Absima Power Tank 4S LiPo battery with a capacity of 6200 mAh and a nominal voltage of 14.8 V supplies the electrical system. The sensors of the MXcarkit are partially replaced and extended.

Component	Model
Chassis	Inferno GT
Motor	Kyosho Speed House Torx 8+
Battery	Absima Power Tank, 4S LiPo

Table 2.1.1: Vehicle Components

2.1.1 Sensor Technology

For the central processing unit an NVIDIA Jetson Orin is installed. It computes all algorithms and controls on board. The communication between the processor and the vehicle actuators is handled by an FSESC 4.12 microcontroller, based on the open-source Vedder Electronic Speed Controller (VESC) 4.12 project [Cho20]. The VESC receives the demanded steering wheel angle and the target velocity and converts it internally into a target rotations per minute (rpm). The speed is currently controlled by a PID controller in the VESC. In future work, the speed-based control is to be converted to torque-based control. The VESC is connected with the Orin via a micro-USB at a clock rate of 100Hz.

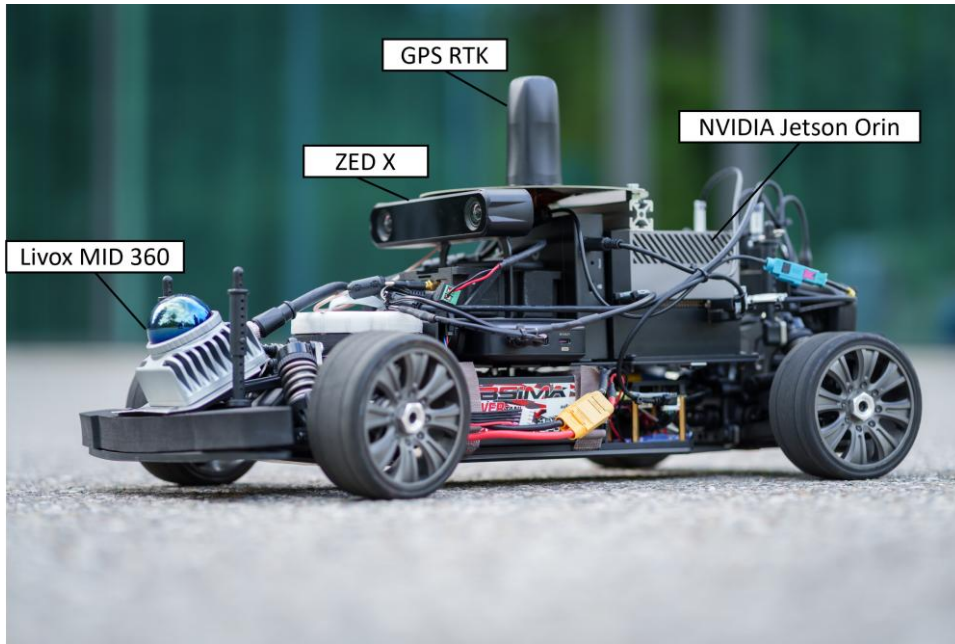


Figure 2.1: MiniAFM with sensor technology

For the environment detection a ZED X stereo camera is installed. It provides both RGB images and depth information of the surrounding. In addition, a Livox MID 360 Light Detection and Ranging (LiDAR) sensor is used for the 3D environment detection. It provides point cloud data of the environment at a sampling rate of 100Hz .

For the determination of the vehicle position different approaches are used, depending on if it is operating inside or outside of buildings. Indoors the Simultaneous Localisation and Mapping (SLAM) Algorithm is used based on the GLIM [Koi24] implementation. It processes the cloud data from the LiDAR, mapping the environment and providing position information at a clock rate of 20Hz. For outdoor testing a GPS receiver with Real-Time kinematic (RTK) correction determines the position. Compared to the SLAM approach, this positioning is 80 *ms* faster. For longitudinal control, Hall sensors are installed on the rear wheels to measure the wheel rpm at a clock rate of 1000Hz. All installed sensors and their clock rates are listed in table 2.1.2.

Sensor	Modell	Clock rate
Stereo camera	ZED X	30 Hz
LiDAR	Livox MID 360	100 Hz
GPS	simpleRTK3B Pro	100 Hz
Wheel sensors	Hall sensors	1 GHz
SLAM	GLIM	20 Hz

Processor	NVIDIA Jetson Orin	2.2 GHz
Microcontroller	FSESC VESC 4.12	100 Hz

Table 2.1.2: Sensors with its Clock Rates on the miniAFM

2.1.2 Simulation model

The simulation model of the miniAFM used throughout this thesis was developed by Rein in Dymola within the Vehicle Dynamics Control Workbench [Bre25], an open Source Dymola Library. It represents a planar double track formulation with linear tire friction and is available in two forms. This section provides a brief description of the model structure and its integration into the simulation environments used in the upcoming chapters.

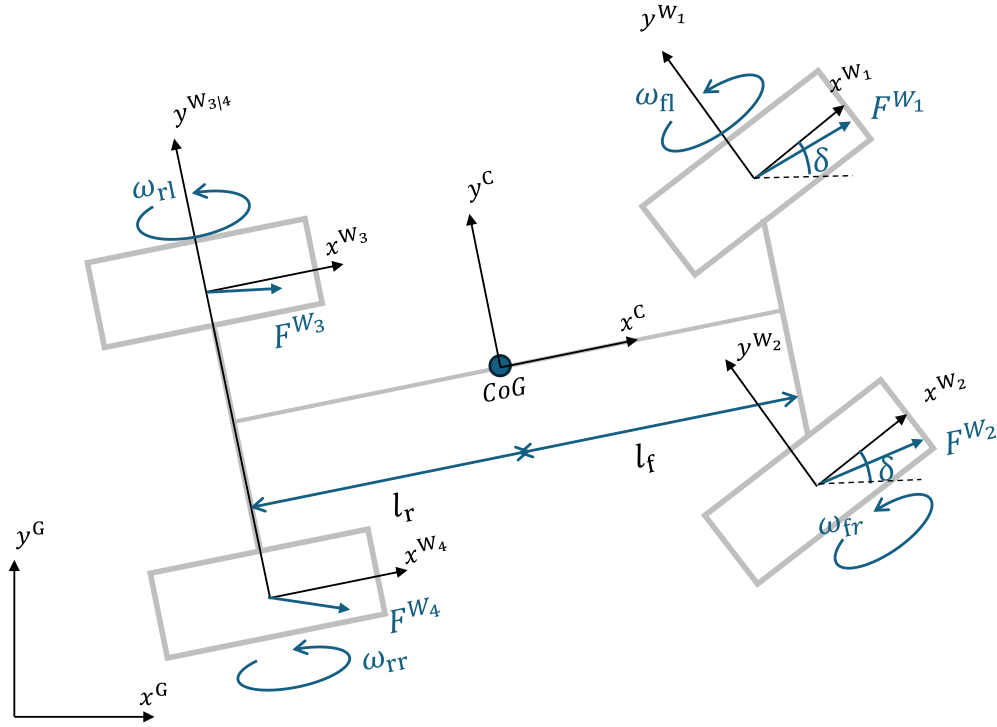


Figure 2.2: Mapping of the Planar Movement on the miniAFM.

Model Equations

In the following, the kinematic and dynamic model equations of the vehicle are derived, that form the basis for the upcoming implementations of the simulation model.

The model is a planar double track formulation with a linear tire friction model. The vehicle state vector contains the variables:

$$\mathbf{x} = x^G, y^G, \psi^G, v_x^C, v_y^C, \dot{\psi}^G, \omega_{fl}, \omega_{fr}, \omega_{rl}, \omega_{rr} \quad (2.1)$$

Here x^G and y^G are the positions of the vehicle in the global frame G with the yaw angle ψ^G and yaw rate $\dot{\psi}^G$, The longitudinal and lateral velocities v_x^C and v_y^C in the car fixed frame C, and the rotational speed ω of all four wheels.

The input vector consists of the steering demand δ_{demand} and the torque demand τ_{demand}

$$\mathbf{u} = \delta_{\text{demand}}^C, \tau_{\text{demand}}^C \quad (2.2)$$

In order to obtain the physical quantities on the wheels, the demanded steering angle and torque are transformed to the wheel frame W through a constant steering ratio i_s and the powertrain gear ratio i_g . The torque is distributed equally among all four wheels.

$$\delta^W = \delta_{\text{demand}}^C \cdot i_s \quad (2.3)$$

$$\tau^W = \tau_{\text{demand}}^C \cdot i_g \quad (2.4)$$

The Tire forces arise from the slip between each wheel and the surface. The longitudinal slip arises when the wheels speed differs from its translational velocity, common during braking or acceleration. The lateral slip arises whenever the wheel moves sideways

$$v_{\text{slip},x} = v_x^W - r \cdot \omega_i \quad (2.5)$$

$$v_{\text{slip},y} = v_y^W \quad (2.6)$$

Here v_x^W , v_y^W are the longitudinal and lateral velocity in each wheel frame W, r the wheel radius and ω_i the associated angular velocity of wheel i . The combined slip magnitude follows as:

$$v_{\text{slip}} = \sqrt{v_{\text{slip},x}^2 + v_{\text{slip},y}^2} \quad (2.7)$$

Proportional to the slip velocity is the total friction force at the contact surface:

$$F_{\text{Total}} = -F_N \cdot \mu \cdot v_{\text{slip}} \quad (2.8)$$

With the normal Force F_N assumed as one quarter of the vehicle weight and μ as the friction coefficient. The total Force is distributed along the slip directions, obtaining the longitudinal and lateral components by projecting along the slip directions

$$F_x^W = F_{\text{Total}} \cdot \frac{v_{\text{slip},x}}{v_{\text{slip}}} \quad (2.9)$$

$$F_y^W = F_{\text{Total}} \cdot \frac{v_{\text{slip},y}}{v_{\text{slip}}} \quad (2.10)$$

Knowing the forces acting on each wheel the associated yaw moments can be determined:

$$M_{fl} = F_{y,fl}^W \cdot l_f - F_{x,fl}^W \cdot \frac{w}{2} \quad (2.11)$$

$$M_{rl} = -F_{y,rl}^W \cdot l_r - F_{x,rl}^W \cdot \frac{w}{2} \quad (2.12)$$

The right-side wheels follow analogously with changed sign of the longitudinal force.

With all wheel forces and moments known the planar vehicle movement equations based on the Newton–Euler formulation can be solved

$$\dot{v}_x^C = \frac{1}{m} \cdot \sum_{i=1}^4 F_{x,i}^W \quad (2.13)$$

$$\dot{v}_y^C = \frac{1}{m} \cdot \sum_{i=1}^4 F_{y,i}^W \quad (2.14)$$

$$\ddot{\psi}^C = \frac{1}{J_\psi} \cdot \sum_{i=1}^4 M_i \quad (2.15)$$

The global position derivatives are obtained by rotating the body-frame velocities into the global frame.

$$\dot{x}^G = \cos(\psi^G) \cdot v_x^C - \sin(\psi^G) \cdot v_y^C \quad (2.16)$$

$$\dot{y}^G = \sin(\psi^G) \cdot v_x^C + \cos(\psi^G) \cdot v_y^C \quad (2.17)$$

For the simulative evaluation of the controllers developed in this thesis, this Dymola model is exported as a FMU and integrated into the Simulink environment. The FMU acts as the plant model within the closed-loop simulation, providing the vehicle state at each time step while the controllers compute the steering angle. In addition, the model is also provided as a standalone Matlab function necessary for the upcoming predictive Stanley controller in chapter 3.3. A list of the vehicle parameter and its values are listed in Table A.1.1.

2.2 Current path following controller of the miniAFM

The path following controller currently used on the miniAFM was originally developed for DLR's ROboMObil, an over-actuated electric Vehicle with four independently steered and driven wheels [Rit15]. The path following control is divided into two stages:

the Time Independent Path Interpolation (TIPI) and a trajectory tracking controller. Combined the controller is referred to as the geoPFC.

2.2.1 Time Independent Path Interpolation

The following method determines the optimal vehicle projection on the reference path and transforms the geometric path representation into time-independent set-points

Motion demand representation

The desired vehicle motion is represented as a function of the arc length $\lambda(s) \in R^5$. The vector contains the reference path represented by the scalar quantities, path position $\mathbf{p}_p^G(s) \in R^2$, orientation $\psi_p^G(s)$, curvature $\kappa_p(s)$ and the longitudinal reference velocity $v_p(s)$ along the path tangent $\mathbf{x}^P$. Noting that the partial derivatives of position and orientation are implicitly contained in the motion demand

$$\frac{d}{ds} \mathbf{p}_p^G(s) = (\cos \psi_p^G(s), \sin \psi_p^G(s))^T \quad (2.18)$$

$$\frac{d}{ds} \psi_p^G(s) = \kappa_p(s) \quad (2.19)$$

This representation can be defined independent of a time schedule thus the motion demand can be planned offline as a purely geometric object.

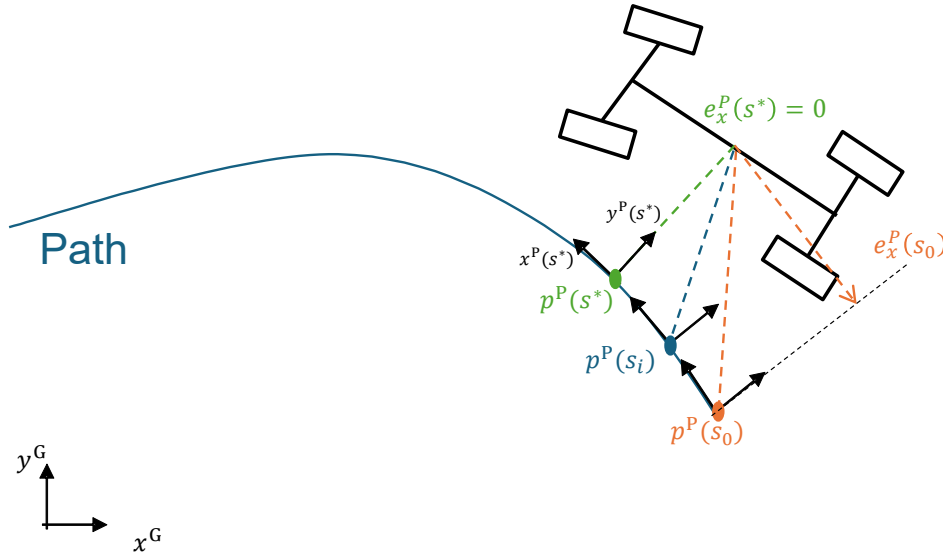


Figure 2.3: Dynamic Root finding process. Starting from the initial guess s_0 converging to s^* .

Arc length determination

Although the motion demand provides the necessary set-points it does not provide which point on the path correspond to the vehicle's current position. The central task of the TIPI

is finding the arc length parameter s^* that minimizes the lateral displacement. The ideal case would be that the vehicle is on the path, then $\mathbf{p}_P^G(s^*) = \mathbf{p}_c^G$. If not, the parameter is searched by projecting the vehicle position $\mathbf{p}_c$ orthogonally onto the reference path.

$$s^* = \operatorname{argmin} || \mathbf{p}_P(s) - \mathbf{p}_c ||_2 \quad (2.20)$$

The solution lets the tangential displacement vanish $e_x^P(s^*) = 0$. The projection exists as long as $e_{\text{lat}}(s^*) \leq \frac{1}{\kappa(s^*)}$ [Pas08]. With the lateral error defined in the path frame as

$$e_{\text{lat}} = [-\sin(\psi_{\text{path}}), \cos(\psi_{\text{path}})]^T \cdot (\mathbf{p}_P(s) - \mathbf{p}_c) \quad (2.21)$$

Trying to solve Eq. (2.20) without iterative methods a dynamic root finding approach is used [Rit15]. The idea is to spread the convergence across consecutive control cycles to drive the tangential error towards zero. With the parameter K_P the control law follows as

$$\dot{s} = -K_P \cdot e_x^P \quad (2.22)$$

To ensure this control law under real driving conditions a feedforward term $\hat{s}$ is added. The feedforward term is derived geometrically under the assumption that the optimal parameter s^* is known. The motion of the reference point along the path can be regarded as a sequence of motions along the tangent of a circle with radius r_p . Similarly for the vehicle motion with the same center and the radius r_c . For the tangential error e_x^P remain zero the center of these circles, the reference point $\mathbf{p}_P(s^*)$ and the vehicle position $\mathbf{p}_c$ must stay on a line. Applying the intercept theorem to this configuration the basic estimation equation follows [Rit15]

$$\dot{s} \cdot r_c = v_{x,veh}^G \cdot r_p \quad (2.23)$$

With $v_{x,veh}^G$ as the tangential component of the vehicle velocity in the global frame.

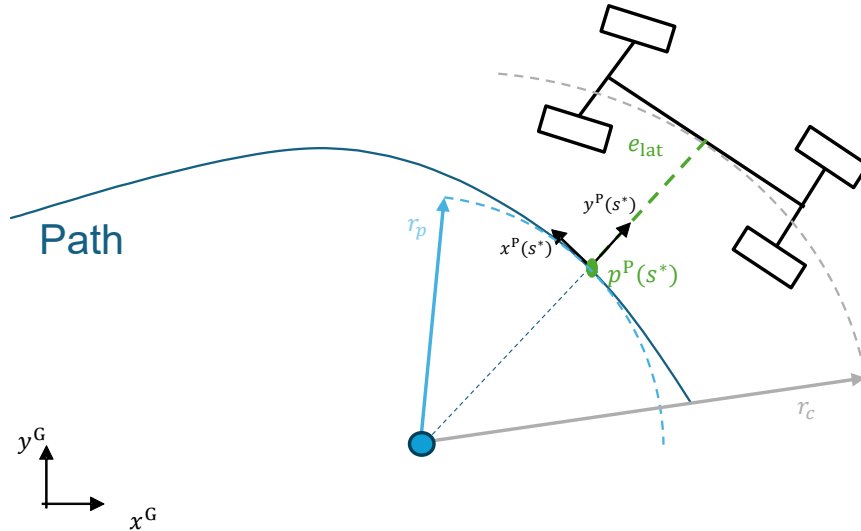


Figure 2.4: .Display of the radii r_p , r_c and its relations.

Expressing the radii using the path curvature and the lateral error leads to

$$r_p = \frac{1}{\kappa(s^*)} \quad (2.24)$$

$$r_c = r_p + e_{lat} = \frac{1}{\kappa(s^*)} + e_{lat} \quad (2.25)$$

With these relations and replacing the unknown optimal parameter s^* by the available arc length s the feedforward Eq. 2.23 gives

$$\hat{s} = \frac{v_{x,veh}^P}{1 + \kappa(s) \cdot e_{lat}} \quad (2.26)$$

Adding $\hat{s}$ to the dynamic root approach the equation follows as

$$\dot{s} = K_P \cdot e_x^P + \frac{v_{x,veh}^G}{1 + \kappa(s) \cdot e_{lat}} \quad (2.27)$$

The actual arc length s is then determined by discrete time integration.

Online trajectory interpolation

The motion demand provides the set-points as functions of arc length, but the tracking controller requires their time derivatives. The TIPI solves this problem by expressing s as a function of time and applying the chain rule [Rit15].

$$\dot{\lambda}(t) = \frac{\partial}{\partial s} \lambda(s(t)) \cdot \dot{s}(t) \quad (2.28)$$

$$\ddot{\lambda}(t) = \frac{\partial^2}{\partial s^2} \lambda(s(t)) \cdot \dot{s}^2 + \frac{\partial}{\partial s} \lambda(s(t)) \cdot \ddot{s} \quad (2.29)$$

Only the first-order derivative is computed while the second-order derivatives are approximated numerically using DT1 filters. [Rit15] Through this mechanism the TIPI transforms the path following problem into a trajectory tracking problem.

2.2.2 Control Algorithm

With the TIPI delivering the motion demand at the optimal reference point, the tracking controller can start to compensate the lateral error, Eq. 2.21, and the orientation error ψ , Eq. 2.30.

$$\psi = \psi_p - \psi_c \quad (2.30)$$

The control law is formulated to be compatible with the geometric control allocation (GCA) [Bue11]. The GCA accepts the vehicle sideslip angle β and the ICR curvature ρ as speed normalised inputs, thus the need to divide measured velocities by the vehicle

speed is eliminated. This is particularly relevant at low speeds, where such a division would amplify sensor noise and controller stability. As a result, the control law remains well-defined across the entire speed range, including standstill."

First the error dynamics for lateral control are getting speed normalized. Therefore, the first-order error dynamic equation for a generic variable x in eq. (2.31) is applied. Substituting x with the orientation offset ψ and the lateral error e_{lat} , the error dynamics follow analogously in eqs. (2.32) and (2.33).

$$\frac{dx}{dt} = \frac{dx^*}{dt} - \frac{x - x^*}{\tau_x} \quad (2.31)$$

$$\frac{d\psi}{dt} = \frac{d\psi^*}{dt} - \frac{\psi - \psi^*}{\tau_x} \quad (2.32)$$

$$\frac{de_{\text{lat}}}{dt} = \frac{de_{\text{lat}}^*}{dt} - \frac{e_{\text{lat}} - e_{\text{lat}}^*}{\tau_x} \quad (2.33)$$

Here the * marking the reference value.

With the transformation from [Sam94] substituting the vehicle speed $v_{\text{veh}} = \frac{dq}{dt}$ replaces the time t by the vehicle path arc length q and the time constant τ_x by the path constant λ_e or λ_ψ follows

$$\frac{d\psi}{dq} = \frac{d\psi^*}{dq} - \frac{\psi - \psi^*}{\lambda_\psi} \quad (2.34)$$

$$\frac{de_{\text{lat}}}{dq} = \frac{de_{\text{lat}}^*}{dq} - \frac{e_{\text{lat}} - e_{\text{lat}}^*}{\lambda_\psi} \quad (2.35)$$

The next step is to express the left-hand sides of these equations in terms of the demanded sideslip angle β^* and the ICR curvature ρ_{ICR}^* .

Deriving the ICR curvature and the path curvature after Eq. 2.19

$$\rho_{\text{ICR}}^* = \frac{d\psi_c}{dq} \quad (2.36)$$

$$\kappa_p = \frac{d\psi_p}{ds} \quad (2.37)$$

Using this definitions and Eq. 2.30 the orientation offset derivative is

$$\frac{d\psi}{dq} = \kappa_p \frac{ds}{dq} - \rho_{\text{ICR}}^* \quad (2.38)$$

For the lateral error (Eq. 2.21) the derivative is computed using the Jacobian Matrix and Eq.2.37[Rit16]:

$$\frac{de_{\text{lat}}}{dq} = J_{e_{\text{lat}}} \cdot \left(\frac{d\psi_p}{dq} \frac{dx_c}{dq} \frac{dy_c}{dq} \frac{dx_p}{dq} \frac{dy_p}{dq} \right) \quad (2.39)$$

Simplified to [Rit16]

$$\frac{de_{\text{lat}}}{dq} = \frac{ds}{dq} \cdot \kappa_p \cdot e_x^p - \sin \beta^* - \psi \quad (2.40)$$

Eq. 2.38 and 2.40 both depend on the ratio $\frac{ds}{dq}$, using the estimate path parameter $\hat{s}$ (Eq. 2.26). The vehicle's velocity vector can be decomposed into a component along the path tangent and a component along the path normal. With the sideslip angle β^* and the heading error ψ , the angle between the vehicle's velocity direction and the path tangent is $\beta^* - \psi$. The tangential projection is therefore [Rit16]

$$v_{veh,x}^p = \cos \beta^* - \psi \frac{dq}{dt} \quad (2.41)$$

with $\frac{dq}{dt}$ being the absolute vehicle speed. $\frac{ds}{dq}$ is computed placing Eq. 2.42 into 2.27 and dividing by $\frac{dq}{dt}$

$$\frac{ds}{dq} = \frac{\cos \beta^* - \psi}{\kappa_p \cdot e_{\text{lat}} + 1} \quad (2.42)$$

Showing that Eq. 2.38 and 2.40 depend on β^* .

Equating 2.35 and 2.40 with these substitutions

$$a = \frac{de_{\text{lat}}^*}{dq} - \frac{e_{\text{lat}} - e_{\text{lat}}^*}{\lambda_\psi} \quad (2.43)$$

$$b = \frac{\kappa_p \cdot e_x^p}{e_{\text{lat}} \cdot \kappa_p + 1} \quad (2.44)$$

$$\xi = \beta^* - \psi \quad (2.45)$$

follows [Rit16]

$$0 = a + b \cdot \cos \xi + \sin \xi \quad (2.46)$$

After solving Eq. 2.46 analytically and selecting the solution branch with $|\xi| < \pi/2$, the demanded sideslip angle can be computed with Eq. 2.45 [Rit16]:

$$\beta^* = \underbrace{-\ln \left(-\frac{a + \sqrt{a^2 - b^2 - 1}}{b - 1} \right)}_{\xi} \cdot i + \psi \quad (2.47)$$

With $\ln$ as the natural logarithm and i as the imaginary unit. Once β^* is known, ρ^*_{ICR} follows directly from the heading error Eq. 2.34 and 2.36. Also replacing $\frac{ds}{dq}$ with 2.43 gives

$$\rho^*_{ICR} = \frac{\psi - \psi^*}{\lambda_\psi} - \frac{d\psi^*}{dq} + \frac{\kappa_P \cdot \cos \beta^* - \psi}{e_{lat} \cdot \kappa_P + 1} \quad (2.48)$$

The first term reduces the heading error over the path constant λ_ψ . The second term accounts for changes in the reference heading along the path. The third term provides a curvature feedforward, ensuring that the demanded yaw rate matches the turning rate.

The virtual demands β^* and ρ^*_{ICR} describe the desired planar motion of the vehicle body but must be translated into physical actuator commands. On the ROMO, the GCA [Bue11] maps the virtual demands β^* and ρ^*_{ICR} to individual steering angles for all four wheels using the Ackermann conditions. Since the miniAFM has only a conventional steered front axle, this allocation reduces to one steering angle and the corresponding front-wheel velocity. Under zero-slip assumptions, the velocity components at the front axle are

$$v_{x,f} = \cos \beta^* \quad (2.49)$$

$$v_{y,f} = \sin \beta^* + \rho^*_{ICR} \cdot l_f \quad (2.50)$$

With l_f as the distance from the center of gravity to the front axle. The steering wheel angle follows as

$$\delta = \tan^{-1}(v_{y,f}, v_{x,f}) \quad (2.51)$$

3. Stanley-based path following control

Among the various approaches to lateral controllers, the Stanley controller is widely used in the automated path following of autonomous vehicles [Sei23]. Originally developed as part of the 2005 Darpa Grand Challenge and first implemented on Stanford University's autonomous vehicle "Stanley". It was the only one of the 40 participating vehicles that did not miss a control gate during the competition, resulting in Stanford University winning the overall victory [Hof07]. In contrast to model-based control approaches, the Stanley controller does not depend on a detailed vehicle model, but on the feedback of purely geometric deviations between the vehicle state and the reference path. This simple, low-model structure makes the controller particularly suitable for real-time applications and allows it to be implemented efficiently on real vehicles equipped with conventional front-axle steering, which is the vehicle configuration all following controllers assume.

The Stanley controller is frequently used as the base component of the path following control and further developed to increase accuracy thus it forms the basis of the path following control implemented and evaluated in this thesis. Chapter 3.1 first introduces an adaptation to the TIPI, from chapter 2.2, necessary for the Stanley controller introduced in 3.2. Section 3.3 describes a predictive extension to the controller that mimics human behaviour for forward-looking driving. Section 3.4 introduces the kinematic reference model along with the necessary adaptation of the TIPI. Based on this foundation, Section 3.5 describes the enhanced Stanley controller for compensating system delay. The reference point used by each controller is summarized in Table 3.1

Controller	Reference Point
Stanley	Front Axle
Predictive Stanley	Front Axle
Enhanced Stanley	Rear Axle

Table 2.21: Reference Points of the Implemented Path Following Controllers.

3.1 Front Axle TIPI

The TIPI, introduced in Section 2.2.1, determines the current path parameter s^* by minimizing the displacement e_{lat} between the vehicle reference position $\mathbf{p}_c$ and the reference path $\mathbf{p}_P(s)$ [Rit15]

In the original formulation $\mathbf{p}_c$ is the vehicle position at the center of gravity. For the controllers, considered in the chapters 3.2 and 3.3, this choice of reference point is no longer

correct. All Controller treat the front wheels as guiding wheels, which requires that the cross-track error and the heading error are defined with respect to the front axle center [Hof07].

The front axle center position p_f is calculated from p_c using the distance l_f from the center of gravity to the front axle and the vehicle yaw angle ψ :

$$\mathbf{p}_f = \mathbf{p}_c + l_f \cdot [\cos(\psi), \sin(\psi)] \quad (3.1)$$

Replacing $\mathbf{p}_c$ with $\mathbf{p}_f$ in Eq. 2.20:

$$s^* = \operatorname{argmin} || \mathbf{p}_p(s) - \mathbf{p}_f ||_2 \quad (3.2)$$

With this adaptation, the TIPI consistently supplies s^* relative to the front axle center usable for all controllers described in the next chapters.

3.2 Stanley Controller

As introduced in the Introduction of Chapter 3, the following controllers consider vehicles with conventional front-axle steering, where the front wheels serve as the guiding wheels [Hof07]. The Stanley Controller, developed for the DARPA Grand Challenge in 2005 forms the basis for all the further controllers in this chapter [Hof07].

The control is based on two error variables, which are determined relative to the nearest point on the desired path using the front axle TIPI from section 3.1.

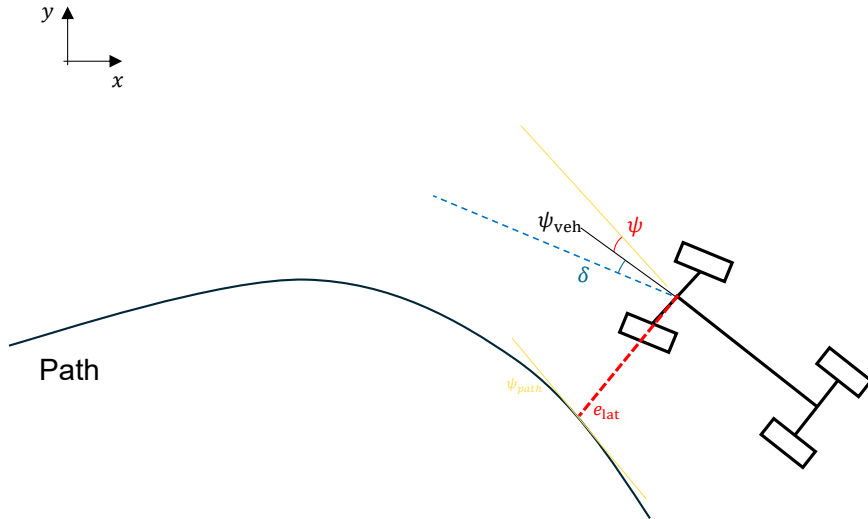


Figure 3.1: Geometric Visualization of the Stanley Controller.

The first error variable is the Heading error ψ . As shown in Figure 3.1 it describes the angle between the orientation of the front wheels and the tangential direction of the

reference trajectory at the nearest point. It ensures that the steered wheels are aligned in the desired direction of travel. If the vehicle behaved ideally, theoretically no further term would be necessary to follow the trajectory, provided there is no offset to the trajectory. It is calculated as the difference between path tangent ψ_{path} and vehicle orientation ψ_{veh} :

$$\psi = \psi_{\text{path}} - \psi_{\text{veh}} \quad (3.3)$$

The second error variable is the lateral error e_{lat} . It describes the shortest distance between the center of the front axle and the nearest point on the reference trajectory (see Figure 3.1) Positive values indicate a deviation to the right of the path and negative values indicate a deviation to the left, consistent with the vehicle coordinate system according to ISO 8855. The calculation follows Eq. 2.11 from Section 2.2.1 Time Independent Path Interpolation.

The steering angle is corrected proportionally to e_{lat} with the parameter K . With increasing speed, the system becomes more sensitive to corrections, which is why they should be reduced at higher speeds. This is achieved by taking the speed v in the denominator. At low speeds, this term can become problematically large and thus react too sensitively. To avoid this, an additional parameter K_{prot} is inserted into the denominator [Hof07], which prevents the gain from exceeding a practical limit as v approaches zero. The arctan function limits the quotient between $\pm 0.5\pi$, which ensures recovery from even infinitely large lateral errors and drive directly towards the trajectory. Once the lateral distance has been reduced sufficiently, the heading error term ψ gradually steers the vehicle back towards the path tangent [Hof07]. Combined the steering wheel angle is calculated with

$$\delta_{\text{calc}} = \psi + \arctan \frac{K \cdot e_{\text{lat}}}{K_{\text{prot}} + v} \quad (3.4)$$

Considering that conventional steering systems have a maximum mechanical range, the steering angle δ is limited to the maximum achievable steering angle δ_{max} . The output is divided into three different regions: a saturated lower region, a saturated upper region and a nominal region [Hof07]. Thus the Stanley control law results to:

$$\delta = \begin{cases} \delta_{\text{calc}} & \text{if } \left| \psi + \arctan \frac{K \cdot e_{\text{lat}}}{K_{\text{prot}} + v} \right| < \delta_{\text{max}} \\ \delta_{\text{max}} & \text{if } \psi + \arctan \frac{K \cdot e_{\text{lat}}}{K_{\text{prot}} + v} \geq \delta_{\text{max}} \\ -\delta_{\text{max}} & \text{if } \psi + \arctan \frac{K \cdot e_{\text{lat}}}{K_{\text{prot}} + v} \leq -\delta_{\text{max}} \end{cases} \quad (3.5)$$

Hoffmann et al. have also implemented additional terms for more dynamic driving situations [Hof07]. The addition addresses yaw rate damping, steering actuator damping and slip angle compensation.

Yaw Rate Damping

At low speeds, the tyres act as natural dampers on lateral forces. However, this damping effect weakens with increasing speed, which can lead to oscillatory yaw behaviour. To counteract this, a corrective steering term is added that is proportional to the difference between the expected yaw rate $\dot{\psi}_{path}$ and the actual vehicle yaw rate $\dot{\psi}_{veh}$ multiplied by the parameter $K_{d,yaw}$ [Hof07]:

$$\delta_{yaw} = K_{d,yaw}(\dot{\psi}_{path} - \dot{\psi}_{veh}) \quad (3.6)$$

Whenever the vehicle yaws faster than anticipated by the path curvature, this term generates a counter-steering command that dampens the motion. The parameter $K_{d,yaw}$ must be chosen large enough to provide effective damping, yet small enough not to negatively affect the tracking performance [Hof07]. The expected yaw rate $\dot{\psi}_{path}$ is calculated either from the derivative of the path trajectory or from the curvature of the path κ and the current speed v .

$$\dot{\psi}_{path} = \kappa \cdot v. \quad (3.7)$$

Steering Actuator Damping

The second addition avoids instabilities caused by delays of the steering actuator. In our nomenclature $\delta(k)$ is the currently measured steering angle and $\delta(k-1)$ is the steering angle measured one time stamp earlier [Hof07]. The parameter $k_{d,steer}$ should be big enough to dampen the steering wheel response but small enough not to impair overall performance [Hof07].

$$\delta_{steer} = k_{d,steer}(\delta(k-1) - \delta(k)) \quad (3.8)$$

Both terms are combined to

$$\delta_{add} = \delta_{yaw} + \delta_{steer} \quad (3.9)$$

Slip angle compensation

The last adjustment is for the correct curve behaviour. The problem is that the steering angle at the output of the Stanley controller is supposed to represent the direction of movement of the vehicle at the front axle. However, this is only true for kinematic

behaviour at low speeds. Lateral forces cause a slip angle, so the direction of movement differs from the geometric wheel direction. Subtracting the stationary yaw angle ψ_{ss} achieve the desired direction of motion without negatively affecting stability.

It is worth noting that this extension introduces a vehicle model into the controller. As stated in the introduction to Chapter 3, the basic Stanley controller is model-free in the sense that it relies solely on geometric error quantities and the measured vehicle speed. The slip angle compensation requires knowledge of vehicle parameters, so the controller is no longer model-free once this term is used.

The steady-state slip angle comes from the linearised single-track model, known as the bicycle model. This model simplifies the four-wheeled vehicle into a flat two-wheel version, with just one tyre at the front and one at the rear. When a vehicle is cornering steadily at a constant speed v and a constant curvature κ , the total lateral forces from both the front and rear axles balance out the centripetal force. Assuming the tyre behaves in a linear way, the lateral force at each axle changes in proportion to its slip angle.

The steady state slip is calculated as [Hof07]:

$$\psi_{ss} = \frac{m}{C \left(1 + \frac{l_f}{l_r}\right)} \cdot v \cdot \dot{\psi}_{path} \quad (3.10)$$

Here, m is the vehicle mass, C is the tire stiffness, l_f and l_r are the distances from the center of gravity to the front and rear axles, v the longitudinal speed and $\dot{\psi}_{path}$ the expected yaw rate.

Putting all these extensions together results the Stanley Law to

$$\delta_{calc} = \Delta\psi + \arctan \frac{K \cdot e_{lat}}{K_{prot} + v} + \delta_{add} \quad (3.11)$$

Here $\psi - \psi_{ss}$ is summarized to $\Delta\psi$.

In summary, the Stanley controller offers clear geometric interpretation, simple implementation and robust control characteristics. However, due to its purely reactive structure, the controller only takes the current vehicle state into account.

3.3 Predictive Stanley Controller

As previously mentioned, the Stanley controller only reduces the error at the current reference point. The predictive Stanley approach addresses this limitation by imitating the forward-looking behaviour of a human driver [Abd20]. The idea is to use a prediction model to extend the control calculation by predictive states.

Starting from the current state the control law is calculated with Eq. 3.5. With the calculated δ the states at the time period $k + 1$ are calculated using the prediction model from Section 2.1.1. For this predicted state, the errors $\Delta\psi$ and e_{lat} are determined using the adapted TIPI from Section 3.1. The steering angle is calculated using the control law with the predicted errors according also to Eq. 3.5 as shown in Figure 3.2.

Here δ_k is the Stanley control angle, computed from the heading error ψ_k , the lateral error $e_{\text{lat},k}$, and the vehicle speed v_k all at the time step k

This process is repeated N times with the time step size Δt , to get the wished length of the prediction Horizon T_{pred} .

$$T = N \cdot \Delta t \quad (3.12)$$

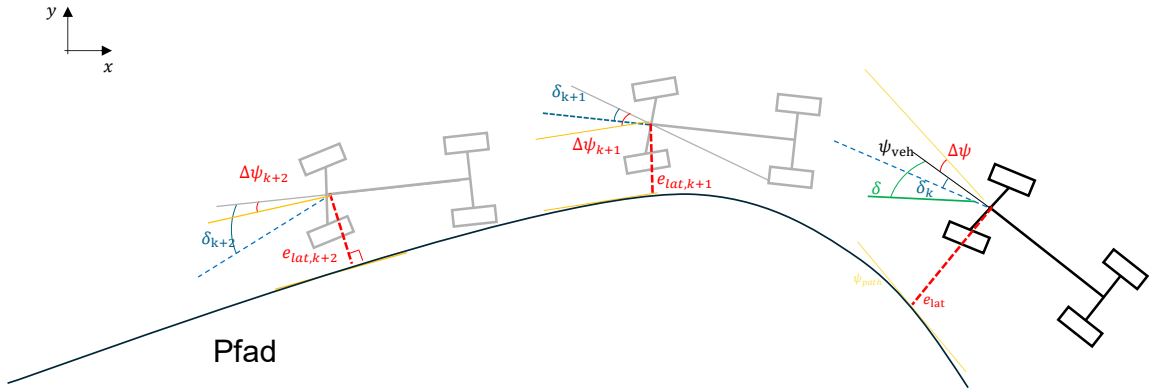


Figure 3.2: Visualization of the predictive Stanley controller. The current vehicle state is shown in black, while the predicted future states are depicted in grey. The green steering angle δ represents the final steering angle derived from the weighted prediction horizon.

The final steering angle is received by the weighted sum of all individual control angles δ_k :

$$\delta = \sum_{k=0}^N K_k \cdot \delta_k \quad (3.13)$$

The weighting factors K_k determine the influence of the individual prediction steps on the total control angle. Typically, K_0 is chosen to be highest for the current state, while the weights for predicted states decrease progressively. The overall sum of the weights should be one.

$$\sum_{k=0}^N K_k = 1 \quad (3.14)$$

3.4 Reference Model for the enhanced Stanley controller

While the previous controllers use the front axle center for the reference point calculation the enhanced Stanley controller, introduced in Chapter 3.5, controls the rear axle center to follow the path, requiring a corresponding adaptation of the TIPI [Sei23]

Rear Axle TIPI

The TIPI calculation is adapted in the same manner as before in 3.1, but now with respect to the rear axle center $\mathbf{p}_r$:

$$\mathbf{p}_r = \mathbf{p}_c - l_r \cdot [\cos(\psi), \sin(\psi)] \quad (3.15)$$

Adapting Eq. 2.7 for s^* :

$$s^* = \operatorname{argmin} ||\mathbf{p}_p(s) - \mathbf{p}_r||_2 \quad (3.16)$$

This adaptation of the TIPI enables the geometric tracking reference for the rear axle.

Kinematic Bicycle model

Although the rear axle is now used to calculate the reference point on the path, the front wheels remain the guiding wheels. Therefore, the Stanley control law from Eq. 3.5 requires the cross-track error and the heading error at the front axle as inputs. These front axle setpoints are not directly available from the path reference point $P_{r,\text{ref}}$ and must be derived.

To correctly determine the front axle reference position a dynamic single-track model is projected onto the path as a reference vehicle [Sei23]. Given $P_{r,\text{ref}}$ on the path, the front axle reference position $P_{f,\text{ref}}$ and the kinematic reference steering angle δ_{ref} are derived such that the rear axle of the reference vehicle follows the path exactly, taking into account the rear axle slip angle $\psi_{ss,r}$. Calculated similar to Eq 3.10 but flipping the ratio of l_f and l_r :

$$\psi_{ss,r} = \frac{m}{C \left(1 + \frac{l_r}{l_f}\right)} \cdot v \cdot \dot{\psi}_{\text{path}} \quad (3.17)$$

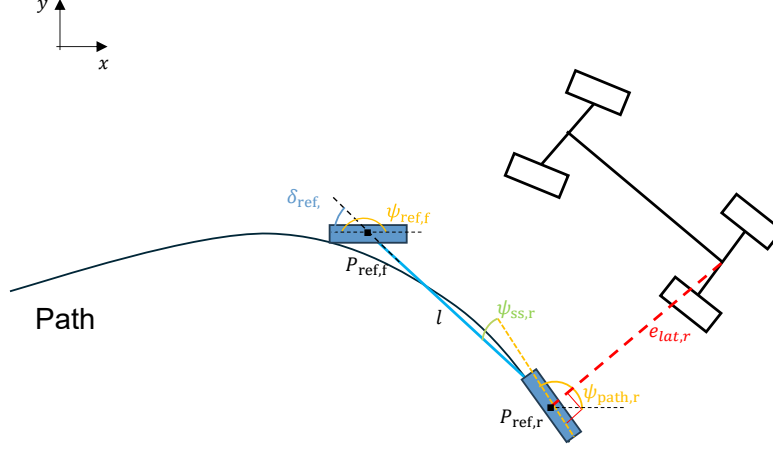


Figure 3.3: The rear axle center of the reference model on the path with tangential orientation $\psi_{\text{path},r}$. Due to the rear axle slip angle $\psi_{ss,r}$, the vehicle orientation deviates from the path tangent. The front axle center $P_{\text{ref},f}$ results from the wheelbase l , the path tangent $\psi_{\text{path},r}$, and the slip angle $\psi_{ss,r}$

The coordinates of the front axle center of the reference vehicle are calculated considering the wheelbase l and the stationary slip angle of the rear axle as follows:

$$\begin{aligned} x_{f,\text{ref}} &= x_{r,\text{ref}} + l \cdot \cos(\psi_{\text{path},r} + \psi_{ss,r}) \\ y_{f,\text{ref}} &= y_{r,\text{ref}} + l \cdot \sin(\psi_{\text{path},r} + \psi_{ss,r}) \end{aligned} \quad (3.18)$$

In addition to the position, the direction of movement of the front reference point is needed. To determine this, the kinematic reference steering angle is required, which results from the path curvature and describes the proportion of the steering angle that results solely from the geometry of the curve [Sei23].

The derivation is based on the consideration of the instantaneous center of rotation (ICR). The distance between ICR and the rear reference point is the curve radius and is derived from the path curvature as follows [Sei23]:

$$r_{r,\text{ref}} = \frac{1}{\kappa_{\text{ref}}} \quad (3.19)$$

An auxiliary variable h can be expressed both via the kinematic reference steering angle and via the slip angle, where the slip angle is defined as in equation 3.6:

$$h = r_{r,\text{ref}} \cdot \cos(\psi_{ss,r}) \quad (3.20)$$

$$h = \frac{l - r_{r,\text{ref}} \cdot \sin \psi_{ss,r}}{\tan \delta_{k,\text{ref}}}$$

Equating and solving gives the kinematic reference steering angle:

$$\delta_{\text{ref}} = \arctan \frac{l \cdot \kappa_{\text{ref}} - \sin(\psi_{ss,r})}{\cos(\psi_{ss,r})} \quad (3.21)$$

The direction of movement of the front reference point is then calculated as the sum of the path tangent, the slip angle and the kinematic steering angle:

$$\psi_{\text{ref},f} = \psi_{\text{path},r} + \psi_{ss,r} + \delta_{\text{ref}} \quad (3.22)$$

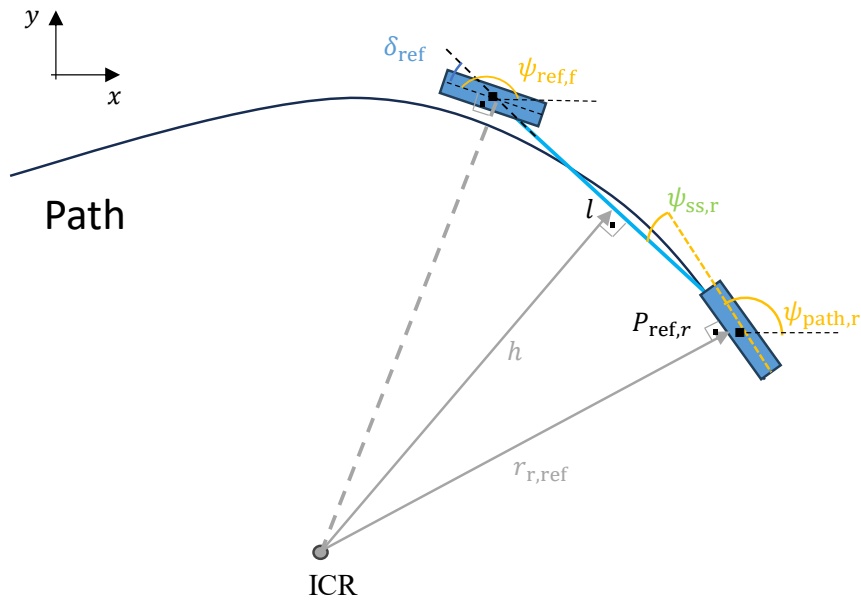


Figure 3.4: Reference vehicle position and orientation. With the instant center of rotation, the curve radius $r_{r,\text{ref}}$ and the auxiliary variable h

3.5 Enhanced Stanley Controller

With the established rear axle reference point and the reference model before, the enhanced Stanley controller can now be formulated. The following sections describe the Stanley law with the new definitions of the error variables. The enhanced Stanley for delay compensation is introduced in Section 3.5.2.

3.5.1 Reformulated Stanley Law

For the Stanley control Law, the lateral error is described no longer as the lateral deviation between the actual and reference point but the reference front axle center point

$$e_{\text{lat},f} = (y_{\text{ref},f} - y_{\text{veh},f}) \cos \psi_{\text{ref},f} - (x_{\text{ref},f} - x_{\text{veh},f}) \sin \psi_{\text{ref},f} \quad (3.23)$$

The heading error is also defined differently in this context. It refers to the difference between the desired direction of movement at the front axle center and the current vehicle orientation:

$$\psi_f = \psi_{\text{ref},f} - \psi_{\text{veh}} \quad (3.24)$$

With these new error definitions, the Stanley control law takes the following form:

$$\delta = \psi_f + \arctan \frac{K \cdot e_{\text{lat},f}}{K_{\text{prot}} + v_r} + \delta_{\text{add}} \quad (3.25)$$

Although the control law has the same algebraic form, the tracking behaviour differs from the basic Stanley controller, since the error quantities are now derived through the reference vehicle model from Chapter 3.4 rather than from a purely geometric nearest-point projection.

3.5.2 Enhanced Stanley Law

To derive the enhanced Stanley Law Eq. 3.22 is inserted into the definition of the heading error, Eq. 3.24, thus it can be broken down into two separate parts:

$$\psi_f = \psi_{r,\text{ref}} + \psi_{ss,r} - \psi_{\text{veh}} + \delta_{\text{ref}} \quad (3.26)$$

The first three summands are combined to form ψ_r^* , the actual orientation error of the vehicle, taking into account the stationary slip [Sei23]:

$$\psi_r^* = \psi_{\text{path},r} + \psi_{ss,r} - \psi_{\text{veh}} \quad (3.27)$$

With this decomposition, Stanley's law takes the following form:

$$\delta = \delta_{\text{ref}} + \psi_r^* + \arctan \frac{K \cdot e_{\text{lat},f}}{K_{\text{soft}} + v_{\text{veh}}} + \delta_{\text{add}} \quad (3.28)$$

This representation clearly shows the role of separating the terms. δ_{ref} depends exclusively on constant vehicle parameters, the current speed v and the path curvature κ . It is independent of the current vehicle state, which makes it a feedforward controller term. This isolation is only possible by projecting the dynamic single-track model onto the path.

The idea of the enhanced Stanley is to use the δ_{ref} as an independent feedforward term to compensate the delay effects of the vehicle system. The feedforward steering angle is no longer calculated with the path parameters at $P_{\text{ref},r}$ but at the predicted point $P_{\text{ref},ff}$, calculated by moving along the path by an arc length s_{ff} , as shown in Figure 3.5 [Sei23].

The feedforward distance s_{ff} is calculated through a constant feedforward time t_{ff} and the current vehicle velocity:

$$s_{ff} = v_{veh} \cdot t_{ff} \quad (3.29)$$

Considering this modification, the feedforward steering angle $\delta_{ref,ff}$ is calculated analogue to equation (3.13):

$$\delta_{ref,ff}(t) = \arctan \frac{l \cdot \kappa_{ref,ff} - \sin \psi_{ss,r}}{\cos \psi_{ss,r}} \quad (3.30)$$

The offset distance s_{ff} is calculated through a constant feedforward time t_{ff} and the current vehicle velocity:

Replacing the original reference angle with the feedforward variant results in the complete control law of the Enhanced Stanley:

$$\delta_{Enhanced} = \delta_{ref,ff} + \psi_r^* + \arctan \frac{K \cdot e_{lat,f}}{K_{soft} + v_{veh}} + \delta_{add} \quad (3.31)$$

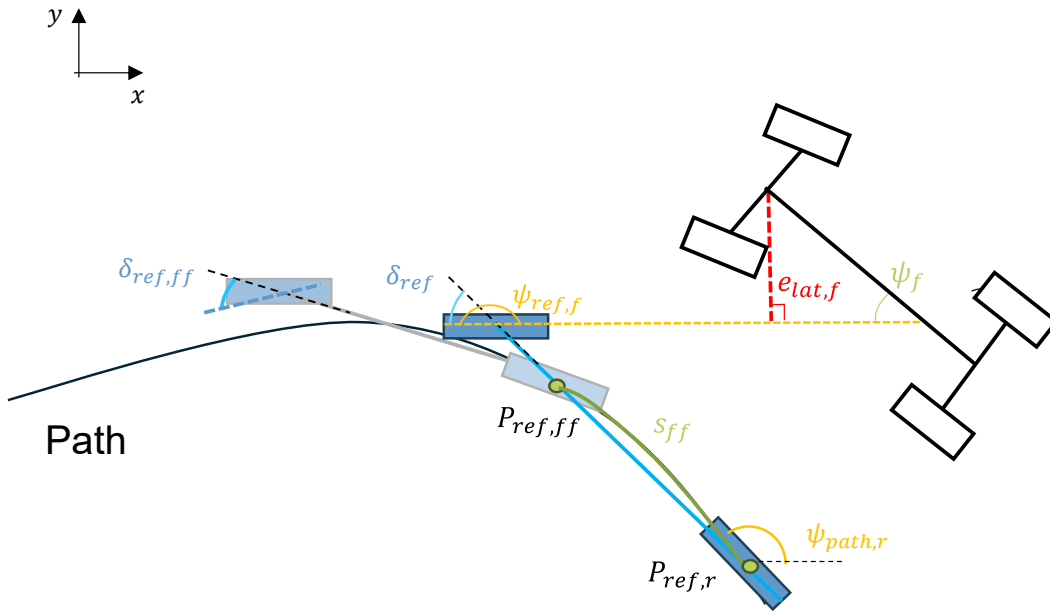


Figure 3.5: Geometry of the Enhanced Stanley controller. The feedforward point $P_{ref,ff}$ is offset from $P_{ref,r}$ by the arc length s_{ff} in the direction of travel, resulting in the feedforward steering angle $\delta_{ref,ff}$.

Note that for $t_{ff} = 0$, the offset s_{ff} vanishes and Eq. 3.31 reduces to Eq. 3.28. Likewise, if the path curvature in the considered section is constant, it is equal to the feedforward curvature so that $\delta_{ref,ff} = \delta_{ref}$. The feedforward time t_{ff} is considered like a control parameter and tuned to counteract the total system delay [Sei23].

4. Simulative Evaluation

The presented controllers from chapter 2.2 and 3 are compared and evaluated using three test scenarios a U-Turn, a double bend curve and a race track. The reference velocity stays consistent through all scenarios at $3 \frac{\text{m}}{\text{s}}$. Control parameters are tuned manually for each scenario to achieve the best possible tracking performance based on the lateral root mean square error (RMSE). For the Predictive Stanley, the weighting factors K_k were not strictly held to Eq. 3.14. In cases where violating the constraint led to a lower lateral RMSE, the constraint was relaxed.

The Simulation uses the double track vehicle model described in chapter 2.1.1. The Simulink solver runs at a fixed step size of 1 ms and the system delay is modelled as discrete delay set to 50 ms , corresponding to the lowest clock rate, which is the SLAM algorithm (see Table 2.1.3).

4.1 Evaluation Criteria

For the quantitative evaluation there are two errors that display the performance of path following controllers. One is the lateral error e_{lat} measuring the distance between vehicle and the reference path. Because the error depends on which reference point each controller regulates onto, a direct comparison is not valid. While the Base Stanley and Predictive Stanley minimize the front axle lateral error, the enhanced Stanley minimize the rear axle lateral error and the geoPFC at the center of gravity (CoG). To remove this inconsistency the lateral error for comparison is evaluated at the cog for all controllers.

The other is the heading error ψ , displaying the angular difference between the vehicle orientation and the reference heading of the path. Defined as Eq. 3.3 it is identical for all reference points.

Over each simulation run we collect the root mean square error (RMSE) to capture the average tracking performance across the entire scenario. The formulas are given as:

$$e_{\text{lat, RMSE}} = \sqrt{\frac{1}{n} \sum_{k=1}^n e_{\text{lat}}^2(k)} \quad (4.1)$$

$$\psi_{\text{RMSE}} = \sqrt{\frac{1}{n} \sum_{k=1}^n \psi^2(k)} \quad (4.2)$$

Because errors are squared before averaging, larger path deviations are penalized more strongly, making the RMSE sensitive to significant tracking errors.

The maximum absolute error captures the single largest deviation, calculated as

$$e_{\text{lat,max}} = \max(|e_{\text{lat}}(k)|) \quad (4.3)$$

$$\psi_{\text{max}} = \max(|e_{\psi}(k)|) \quad (4.4)$$

Together these quantities form the performance indicators for the upcoming test scenarios.

4.2 Test Scenario U Turn

The first and simplest scenario is the U-Turn, testing the controller during a sustained constant curvature segment. The path starts with a 1 m straight, enters a semicircular turn with a constant radius of 1.5 m, and exits onto a 1 m return straight. This scenario allows tracking the steady state accuracy inside a turn. The used parameters for the U-Turn are listed in Table 5.2.2: List of the Control Parameter Set for the U-Turn Scenario.

Results

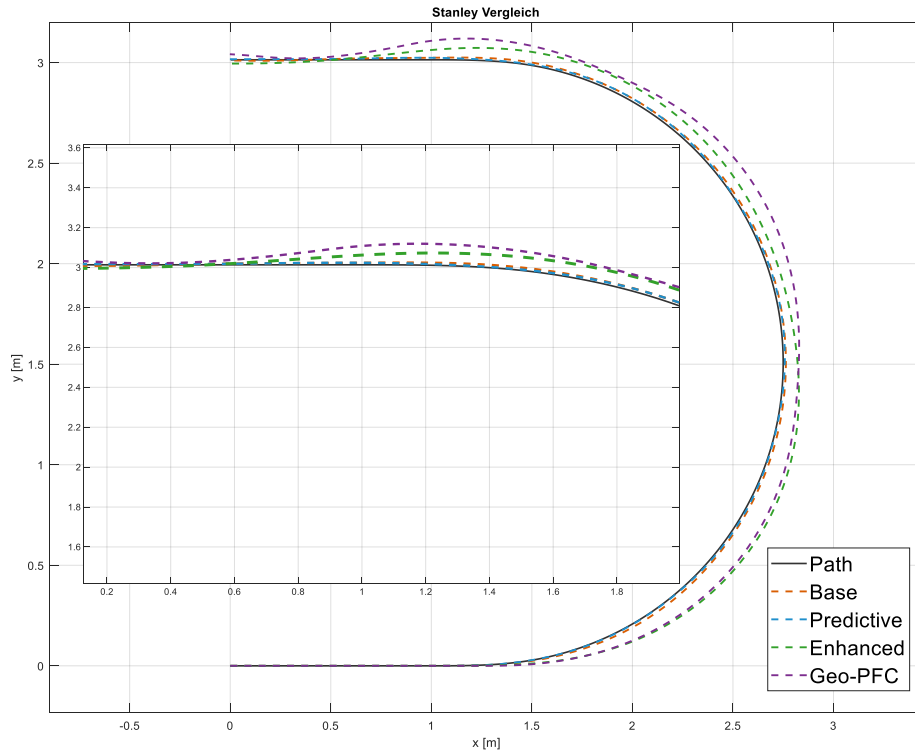


Figure 4.1: Trajectories of the controller on the simulative U-turn test, with extra zoom on the exit of the curve.

Figure 4.1 shows the trajectories on the U-turn. The geoPFC starts with a noticeably lateral offset right from the curve entry and holds this steady state error over throughout the full turn. It does not overshoot the reference path at the exit but starts to counter steer on the straight section. As the current used controller, it sets the benchmark with the lateral RMSE of 75.9 mm and a maximum error of 118.3 mm .

The base Stanley and predictive Stanley track the reference path tighter throughout the entire run. The base Stanley achieves a lateral RMSE 10.9 mm , which is 86% lower than the benchmark. Even lower is the reduction of the predictive with 90%, reaching 6.2 mm . After the turn both converge smoothly back onto the path without overshoots or counter steering.

The enhanced Stanley starts with the largest deviation but reduces it slightly toward the half of the arc. At the curve exit it overshoots and must counter steer to recover. Its lateral RMSE is 16% lower than the geoPFC with 63.8 mm but the maximum error of 127.8 mm exceeds the geoPFC maximum. The error values in Table 4.2.1 confirm this ranking.

Error Controller	e_{lat} RMSE	e_{lat} Max	e_{ψ} RMSE	e_{ψ} Max
geoPFC	$0.0759m$	$0.1183m$	4.77°	10.38°
Stanley Base	$0.0108m$	$0.0165m$	1.71°	3.84°
Stanley Predictive	$0.0062m$	$0.0140m$	1.55°	2.85°
Stanley Enhance	$0.0638m$	$0.1278m$	3.89°	8.64°

Table 4.2.1: Error Values on the U-turn.

4.3 Test scenario double bend

The second scenario tests the controller's response to successive changes. The path is composed from an initial straight of 1 m , a left turning 90 degree arc with radius of $1.5m$, a right turning arc with the same metrics and a final straight of 1 m . Thus, the controller must change between left and right steering demands within short distance. Table A.2.2 lists the control parameters used for the double bend. To avoid oscillation in the double bend, the controller gains had to be reduced noticeably compared to the U-turn configuration. The tighter sequencing of the two curves leaves less time to recover from an aggressive correction, so a more conservative tuning was necessary to keep the response stable.

Results

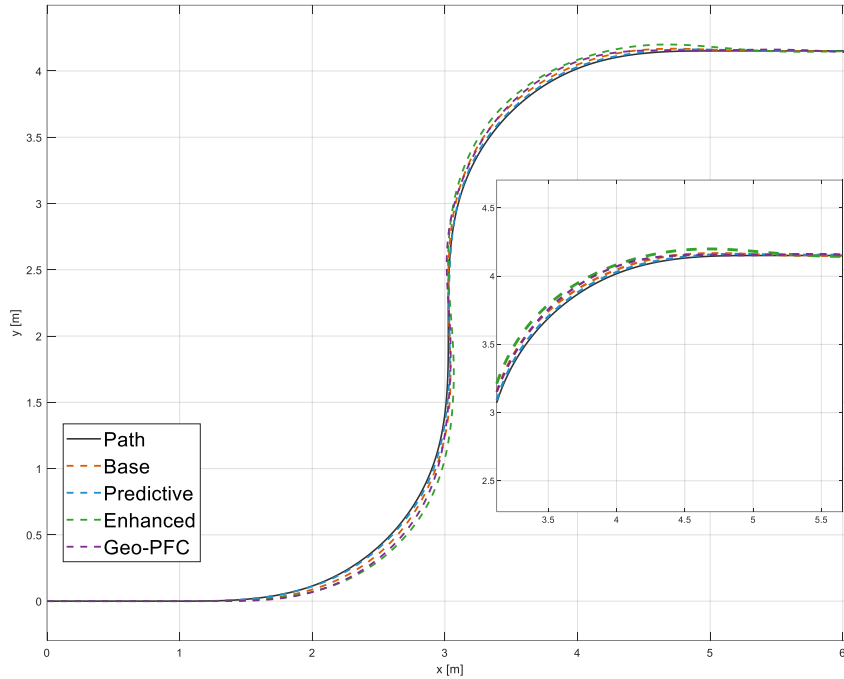


Figure 4.2: Trajectories on the simulative double bend test with zoom in on the second arc towards the end straight.

Figure 4.2 shows the trajectories on the double bend curve. At the curve entry, all four controllers behave as on the U-turn. The geoPFC converges onto the short straight at the in between section and takes the second arc the same as on the U-Turn. With a lateral RMSE of 30.2 mm and a maximum error of 63.9 mm, it sets the benchmark for this maneuver.

The base Stanley stays closer to the reference path than at the beginning but on one short section toward the mid straight it drifts briefly wider. Its lateral RMSE of 20.5 mm is 32% below the geoPFC, and its maximum error of 40.1 mm is 37% lower. The heading RMSE of 2.11° also beats the geoPFC at 3.02° .

The Predictive Stanley converges the fastest onto the short transition straight thus following the second arc the same as the first. Across every metric it leads by a clear margin, with a lateral RMSE of 7.6 mm, which is 75% below the geoPFC, and a maximum error of 12.2 mm that is 78% lower. Its heading RMSE of 1.20° is the lowest of all four controllers.

The enhanced Stanley converges as the last one onto the transition straight. For the arcs it behaves the same as on the U-Turn with the largest lateral deviations and the overshoot at the exit. The ranking is consistent across all metrics listed in table 4.3.1.

Error Controller	e_{lat} RMSE	e_{lat} Max	e_{ψ} RMSE	e_{ψ} Max
geoPFC	0.0302m	0.0639m	3.02°	7.34°
Stanley Base	0.0205m	0.0401m	2.11°	4.49°
Stanley predictive	0.0076m	0.0122m	1.20°	2.36°
Stanley Enhance	0.0449m	0.0924m	3.15°	7.05°

Table 4.3.1: Error Values on the double bend curve

4.4 Test on Race Track

The racetrack combines the challenges of the previous scenarios into a circuit. The path features straight segments, curves with varying radii, a double bend and a U-turn. This variety of path segments tests each controller across all operating conditions within a single set of parameters. The same track is used for the real vehicle testing presented in Chapter 5, where the simulation results are validated against measurements from the physical test vehicle. The control parameters used for the race track evaluation are listed in Table A.2.3. Again, the parameters are lowered to avoid oscillation and the number of predictive steps was increased.

Results

Figure 4.3 shows the racetrack with the resulting vehicle trajectories. The geoPFC produces the largest lateral RMSE across the full circuit at 273.9 mm and sets the benchmark for this scenario. The base Stanley has a lateral RMSE of 86.6 mm, which is 68% below the geoPFC. The enhanced Stanley sits between the two at 169.6 mm, which is 38% below the geoPFC but roughly twice the base Stanley error. Both controllers exceed 200 mm at their peak deviation in the double bend and U-turn section.

The Predictive Stanley is the only controller that stays below 100 mm at the peak, reaching a maximum lateral error of 84.2 mm. Its lateral RMSE of 29.4 mm is 89% below the geoPFC benchmark.

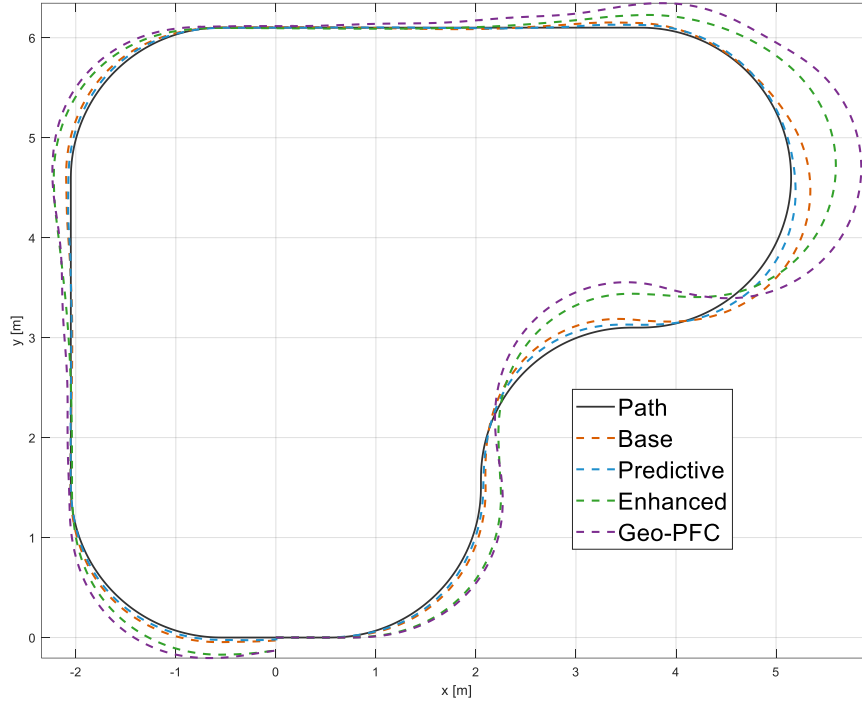


Figure 4.3: Trajectories of the controller on the simulative racetrack.

The heading errors follow the same ranking, with the Predictive Stanley reaching the lowest heading RMSE of all four at 2.71° . The heading peaks occur at the U-turn entry, where the controllers are still correcting the residual error carried over from the double bend. The full error metrics are listed in Table 4.4.1.

Controller \ Error	e_{lat} RMSE	e_{lat} Max	e_{ψ} RMSE	e_{ψ} Max
geoPFC	0.2739m	0.7067m	11.87°	37.99°
Stanley Base	0.0686m	0.2112m	4.48°	13.4°
Stanley predictive	0.0274m	0.0842m	2.71°	7.57°
Stanley Enhance	0.1696m	0.3471m	7.74°	22.2°

Table 4.4.1: Error values on the racetrack.

4.5 Robustness Tests

After the evaluation on the three scenarios the controllers face two robustness tests. The first examines the controllers return onto the path when initialized with an offset. The second assesses the controller sensitivity to increased latency in the control loop.

4.5.1 Robustness to initial Offset

The offset test uses the double bend maneuver with the manual tuned parameters from chapter 4.3. The objective is to see how the controller steers the vehicle back onto the path without extra tuning of the parameters. The offset is initialized as 1 m on the x axis and 1 m on the y axis.

Result

Figure 4.4 shows the resulting trajectories. The base and enhanced Stanley converge the fastest onto the initial straight but both overshoot significantly at the first curve entry. The overshoot carries into the second arc and amplifies through the rest of the path. The enhanced Stanley produces the largest overshoot at the top of the first curve. The geoPFC takes a more conservative return path with less overshoot but oscillates through the entire curve section. The Predictive Stanley takes the longest to converge back onto the path. It cut through the path but then gradually reduces the lateral error and follows the double bend tightly. It is the only controller to follow the double bend satisfyingly with these parameters.

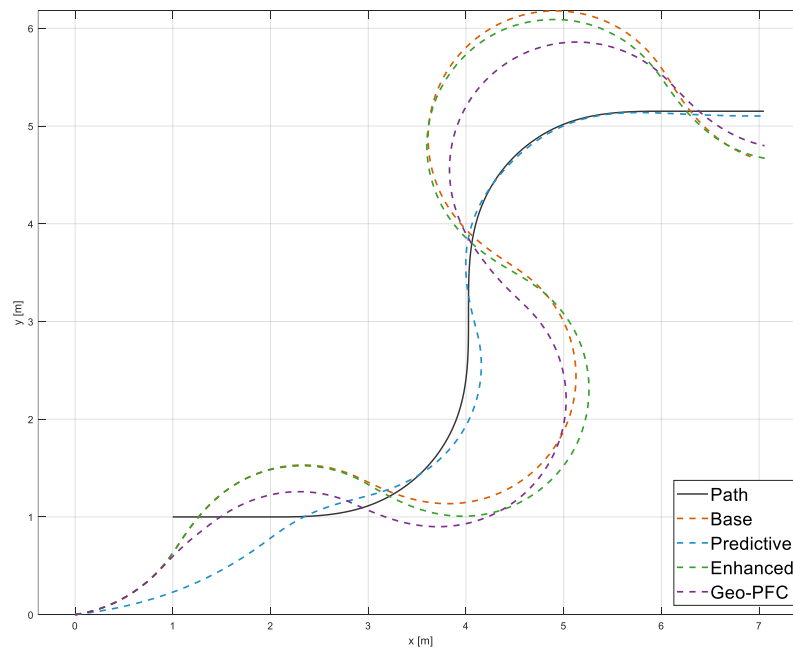


Figure 4.4: Trajectories of the controller compensating the offset.

Parameter Adaption

Reducing gains of each controller (see Table A.2.2) leads to the trajectories in Figure 4.5. All controllers converge consistently onto the initial straight before the curve. The geoPFC converges the fastest. The Stanley controllers follow closely behind. The predictive has the tightest tracking followed by the base Stanley. The enhanced Stanley starts to drift outward through the curve more than the other three. The ranking through the double bend remains the same as in Section 4.2. The error values are not displayed because they are defined mostly through the offset indicating errors.

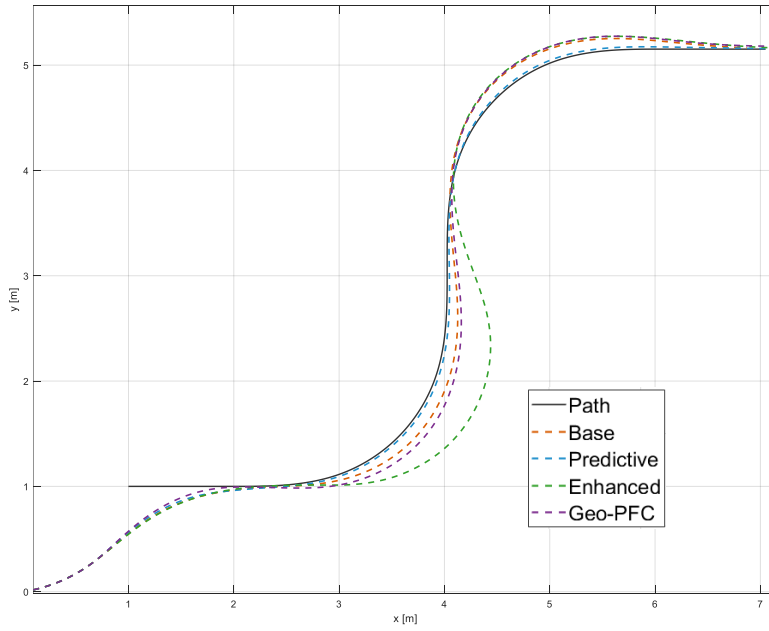


Figure 4.5: Improved trajectories of the controller compensating the offset.

4.5.2 Robustness to system delay

The exact latency of the system is currently unknown, thus we approximate it by the slowest clock rate of the sensors. Since the SLAM module operates at the lowest rate, the latency is set to 50 ms . To ensure the robustness of the system it was tested with simulation delays up to 100 ms and 150 ms . First the simulation is run with parameters the same as on the previous race track test. Afterwards the parameters are tuned for the specific delay.

Latency: 100 ms

Figure 4.6 shows the trajectories with the 100 ms system delay and the original parameters from the race track scenario (cf. table A.2.3). The geoPFC drifts more outwards through every curve and starts to oscillate on the straights. Its lateral RMSE rises 574.3 mm , double the value at 50 ms .

The enhanced Stanley handles the latency growth best even without extra tuning the feed-forward time. Despite performing worst on the previous tests, it has now the smoothest trajectory and the lowest lateral RMSE with 0.3873 m .

The base Stanley settles best on the top straight after an initial correction, though with a lateral RMSE of 0.4603 m . Notable is that the base Stanley follows the last two curves with comparatively little outward drift. Its lateral RMSE places it between the enhanced Stanley and the geoPFC.

The controllers except the enhanced Stanley exceed 1 m maximum lateral error at the U-Turn. The heading errors follow the same ranking as the lateral errors. All values are listed in Table 4.5.1.

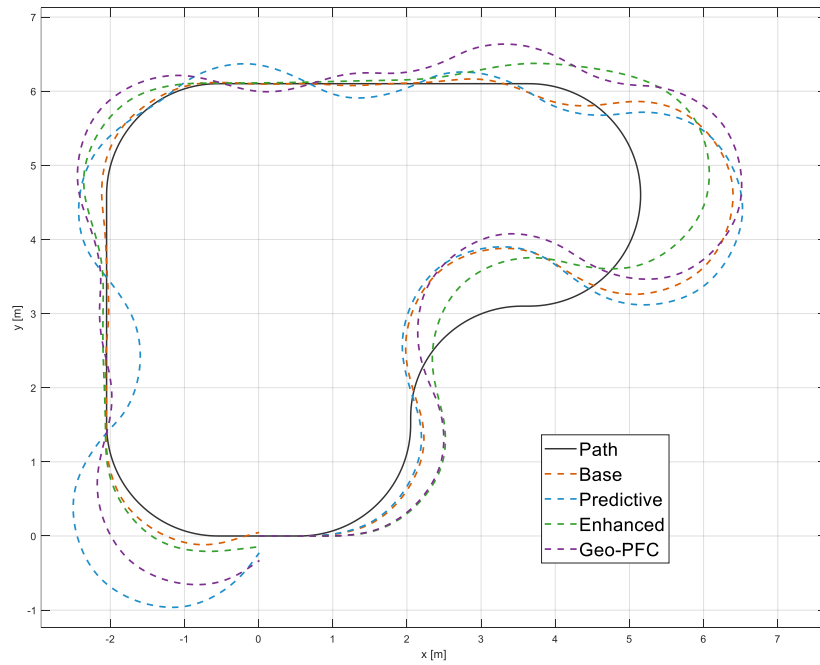


Figure 4.6: Trajectories of the controller with a latency of 100ms .

Error	e_{lat} RMSE	e_{lat} Max	e_{ψ} RMSE	e_{ψ} Max
Controller				
geoPFC	0.5743m	1.3682m	21.3°	66.20°
Stanley Base	0.4603m	1.2450m	20.8°	62.62°
Stanley Enhance	0.3873m	0.9685m	18.2°	55.11°
Stanley predictive	0.6002m	1.3840m	27.6°	68.14°

Table 4.5.1: Error values with a Delay of 100ms .

Parameter Adaptation

In order to improve the tracking performance, the parameters are tuned according to table A.3.2, leading to a switch of the performance ranking. The geoPFC improves the least from the tuning with 28% reduction to 412.7 *mm*, while the predictive Stanley drops the lateral RMSE the most to 159.6 *mm*, reducing it by 74%. The enhanced Stanley follows at 216.0 *mm* tracking tighter than the base Stanley at 249.0 *mm*. Thus the predictive Stanley becomes the best performer with 159.6 *mm*. Notably the enhanced Stanley still stays with the second best performance, better than on the previous tests without latency. It is followed by the base Stanley and resulting in the geoPFC being last. The figure 4.7 shows the resulting trajectories and the table 4.5.3 lists the full results.

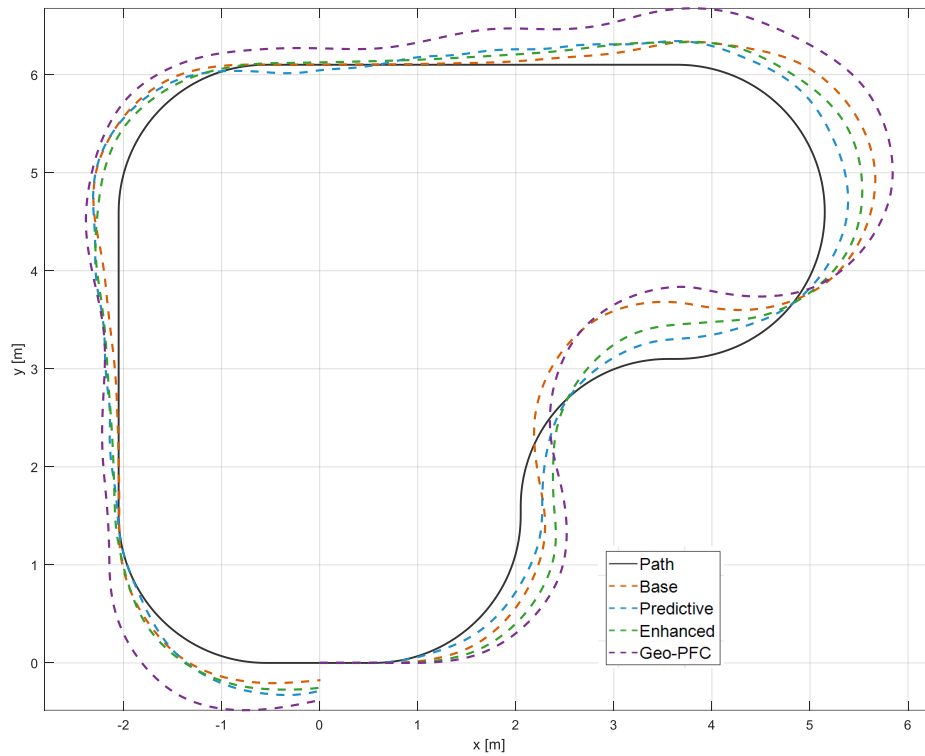


Figure 4.7: Improved trajectories with 100ms system delay.

Controller \ Error	e_{lat} RMSE	e_{lat} Max	e_{ψ} RMSE	e_{ψ} Max
geoPFC	0.4127m	0.7931m	15.82°	44.17°
Stanley Base	0.2490m	0.5437m	12.04°	33.92°
Stanley predictive	0.1596m	0.3016m	7.58°	18.51°
Stanley Enhance	0.2160m	0.4333m	9.33°	25.96°

Table 4.5.2: Improved error values with 100ms delay.

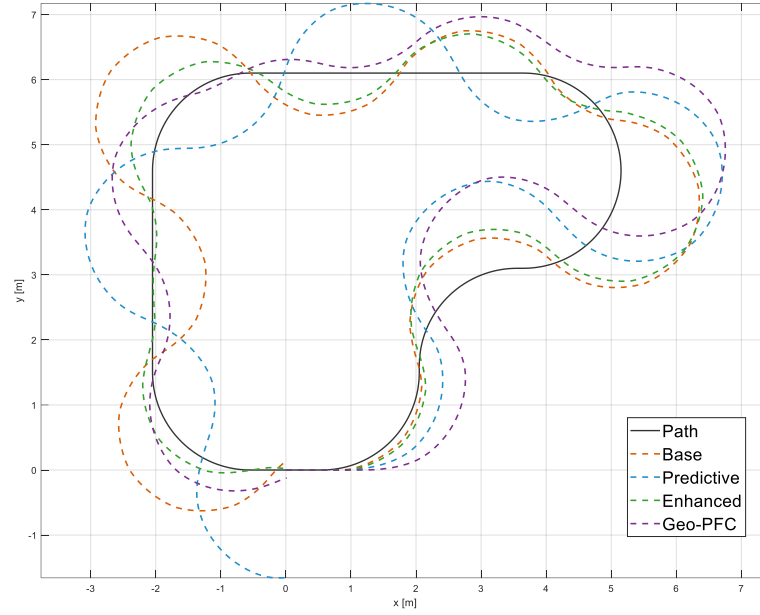
Latency:150ms

Figure 4.8: Trajectories of the controller with a latency of 150ms.

Observing the trajectories in Figure 4.8, with 150 ms system delay the tracking quality degrades further. The good behaviour on straight segments from the base and enhanced Stanley disappeared and all four controllers oscillate through the entire racetrack. The geoPFC achieves a lateral RMSE of 721.7 mm with a maximum lateral error of 1635.3 mm and a heading RMSE of 33.01°. The enhanced Stanley shows the smallest oscillation amplitude on the straights and achieves the best lateral RMSE at 494.1 mm with a maximum lateral error of 1299.5 mm and a heading RMSE of 24.69°. The base Stanley follows with a lateral RMSE of 601.0 mm and a maximum lateral error of 1483.6 mm. The Predictive Stanley remains the weakest at 838.7 mm lateral RMSE with a maximum lateral error of 1658.0 mm and 43.72° heading RMSE. The maximum heading error reaches 100.39° for the geoPFC and 88.82° for the Predictive Stanley. All controllers converge near to the end of the track. However, the predictive controller is the only one that does not return towards the starting point. This results in the enhanced Stanley ranking first, followed by the base Stanley, the geoPFC and the Predictive Stanley as last. Table 4.5.3 lists all error values.

Controller \ Error	e_{lat} RMSE	e_{lat} Max	e_{ψ} RMSE	e_{ψ} Max
geoPFC	0.7210m	1.6350m	33.01°	100.39°
Stanley Base	0.6010m	1.4836m	29.39°	59.98°
Stanley predicitive	0.8387m	1.6580m	43.72°	88.82°
Stanley Enhanced	0.4941m	1.2995m	24.69°	55.33°

Table 4.5.3: Error values with 150 ms delay.

Parameter Adaptation

Figure 4.9 shows the new trajectories with the tuned parameters (see table A.3.3). As well as for the 100ms the predictive Stanley benefits the most from adapting the parameters reducing the lateral RMSE by 72% from 0.8387 m to 0.2358 m. It follows the path through the double bend the tightest but exits the U-turn with the highest deviation. The base Stanley improves by 56% from 0.6010m to 0.2620m. The trajectory looks even though it has a higher RMSE than the predictive more stable converging onto the straight paths and following the final two curves. The enhanced Stanley also reduces its lateral error by 30% to 0.3427m. Its trajectory looks like the base Stanley with a higher drift outwards the curves. The geoPFC benefits the least from the adaption only reducing the error by 22%. Table 4.5.4 lists the full error results.

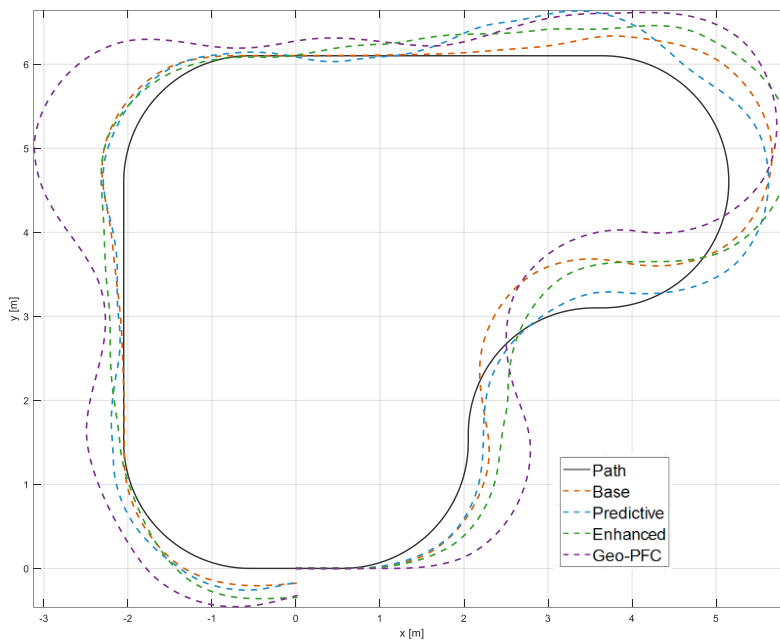


Figure 4.9: Improved trajectories with 150ms delay

Controller \ Error	e_{lat} RMSE	e_{lat} Max	e_{ψ} RMSE	e_{ψ} Max
geoPFC	0.5558m	1.1136m	21.69°	51.03°
Stanley Base	0.2620m	0.5837m	12.04°	14.09°
Stanley predictive	0.2358m	0.5331m	10.36°	28.07°
Stanley Enhance	0.3427m	0.8155m	14.09°	40.78°

Table 4.5.4: Improved error values with 150 ms delay.

4.6 Evaluation

Based on the results from the previous tests the four controllers are evaluated on their overall performance and robustness.

Path tracking

The geoPFC ranks last on the double bend and the race track. On the U-turn it places third. Across all three scenarios a steady-state offset is visible during constant curvature sections, an error that neither the base nor the Predictive Stanley produce. Table 4.6.1 lists the lateral RMSE across the test scenarios.

The Predictive Stanley leads on all three scenarios, reaching a lateral RMSE of 7.6 mm on the double bend, 6.2 mm on the U-turn and 29.4 mm on the race track. The base Stanley follows at roughly double the error values. It handles moderate curvature well but sharp and rapid transitions lead to higher errors than the Predictive Stanley. The Enhanced Stanley ranks third on the U-turn and race track, outperforming the geoPFC on both. Only on the double bend does the geoPFC track tighter than the Enhanced Stanley. Overall the geoPFC finishes last on two of three scenarios. Table 4.6.1 lists the lateral RMSE across the test scenarios.

Test scenario Controller	U-Turn	Double Bend	Race Track
geoPFC	$0.0759m$	$0.0302m$	$0.2739m$
Stanley Base	$0.0108m$	$0.0205m$	$0.0686m$
Stanley Predictive	$0.0062m$	$0.0076m$	$0.0274m$
Stanley Enhanced	$0.0638m$	$0.0449m$	$0.1696m$

Table 4.6.1: Lateral RMSE across the test scenarios with $3 \frac{m}{s}$.

Robustness to initial offset

Observing the offset tests none of the controller could achieve a satisfactory recovery without extra tuning the parameters. The gains that provide good path tracking without offset are too aggressive causing the controllers to overshoot and oscillate. With or without extra tuning, the predictive Stanley still had the best performance followed by the base Stanley.

Robustness to delays

With increasing system delay the geoPFC degrades steadily and benefits the least from retuning the control parameters. Its behaviour stays largely consistent, but the

performance stays below the Stanley based controllers, for both latencies. The predictive Stanley shows the lowest robustness to changes in delay, consistently showing the worst performance without retuning. At the same time it benefits the most from parameter tuning and achieving the tightest tracking afterwards for both delays.

Without extra tuning at 100 ms delay only the base and enhanced Stanley do not oscillate.

The comparison between the Base and Enhanced Stanley is less clear, since both outperform the geoPFC but their relative ranking shifts with the delay. At 100 ms delay, the Enhanced Stanley shows the highest robustness. Without re-tuning it drops from third place at 50 ms to the best performance at 100 ms with a lateral RMSE of 387.3 mm. The Base Stanley follows at 460.3 mm. After parameter tuning, the Predictive Stanley recovers to first place at 159.6 mm. The Enhanced Stanley ranks second at 216.0 mm, followed by the Base Stanley at 249.0 mm, while the geoPFC remains last at 412.7 mm.

At 150 ms delay, the Enhanced Stanley again shows the highest robustness without re-tuning, reaching a lateral RMSE of 494.1 mm against 601.0 mm for the Base Stanley. After tuning the ranking shifts. The Predictive Stanley recovers to first at 235.8 mm. The Base Stanley takes second at 262.0 mm, now ahead of the Enhanced Stanley at 342.7 mm. The geoPFC benefits the least from re-tuning and stays last at 555.8 mm.. The lateral RMSE values across the delays are listed in Table 4.6.2.

Test scenario Controller	50 ms	100 ms	150 ms
geoPFC	0.2739m	0.4127m	0.5558m
Stanley Base	0.0686m	0.2490m	0.2620m
Stanley Predictive	0.0274m	0.1596m	0.2358m
Stanley Enhanced	0.1696m	0.2160m	0.3427m

Table 4.6.2: The improved lateral RMSE across each delay latency.

Conclusion

The geoPFC provides stable tracking, avoiding large errors but having a steady state offset on constant curvatures. This limits its overall performance ceiling compared to the Stanley based controllers.

The predictive Stanley delivers the best tracking when the parameters can be tuned for the specific latency and path following problem. Because it has the most parameters of all four controllers the tuning effort is also the highest but generating the best outcome. The base Stanley is performs well and shows good robustness. It places close behind the

tracking of the predictive Stanley and degrades less under increasing delay. The enhanced Stanley shows no clear advantage over the base Stanley except at 100 *ms* latency, though this may result from suboptimal parameter tuning rather than a fundamental limitation of the controller.

5. Evaluation on the test vehicle

To confirm the previous simulation results a test on the miniAFM under real conditions is evaluated. In this chapter the base Stanley and enhanced Stanley are tested on the miniAFM and compared to the geoPFC controller. The predictive Stanley could not be tested because the prediction model needs the front axle wheel speeds for initializing the prediction (cf. chapter 2.1.2) which are currently not measured on the miniAFM but will be deployed in the future.

5.1 Results

The vehicle drove the racetrack at 1.5 m/s. Two runs were performed with different parameter sets. The first run uses parameters tuned for high tracking performance in simulation. The second run uses reduced gains to address the oscillation observed in the first run. The parameters are listed in Table A.2.4. and A.3.4

High Parameter Set

Figure 5.1 shows the trajectories from the first run. The geoPFC follows the reference path with stable and consistent tracking through the curves. The Base Stanley tracks closest to the reference through the curves but oscillates on the straight segments. The enhanced Stanley shows by far the largest deviations, drifting wide through every curve and losing the path entirely in the double bend and U-turn section. On the straight it also oscillates. Its lateral RMSE of 0.4126 m is nearly three times the geoPFC at 0.1481 m. The base Stanley reaches a lateral RMSE of 0.1745 m, close to the geoPFC, but its heading RMSE of 11.6° is more than double the geoPFC at 5.51°. The oscillation on straights is the main cause to the higher heading error. Table 5.1.1 lists the full results.

Controller \ Error	e_{lat} RMSE	e_{lat} Max	e_{ψ} RMSE	e_{ψ} Max
geoPFC	0.1481 m	0.3127m	5.51°	21.7°
Stanley Base	0.1745m	0.1837m	11.6°	34.6°
Stanley Enhance	0.4126 m	1.3981m	15.2°	39.1°

Table 5.1.1: Error quantities for the evaluation on the vehicle with strong parameters

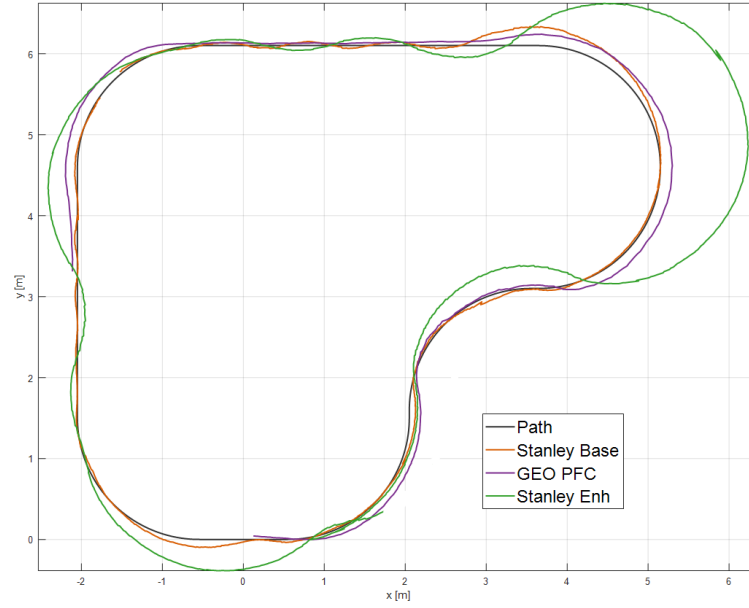


Figure 5.1: Controller trajectories on the race track with High Parameter set.

Parameter Adaptation

Figure 5.2 shows the trajectories after reducing the controller gains. The base Stanley improves significantly. The oscillation on the straights is reduced and the tracking through the curves remains tight. Its lateral RMSE drops to 0.0764 m, roughly half the geoPFC. The heading RMSE drops to 5.1° , now matching the geoPFC level. The enhanced Stanley stops also oscillating but does not improve its lateral RMSE with the adapted parameters. Its lateral RMSE rises slightly to 0.5052 m and the heading error also increases. Table 5.1.2 lists the full results.

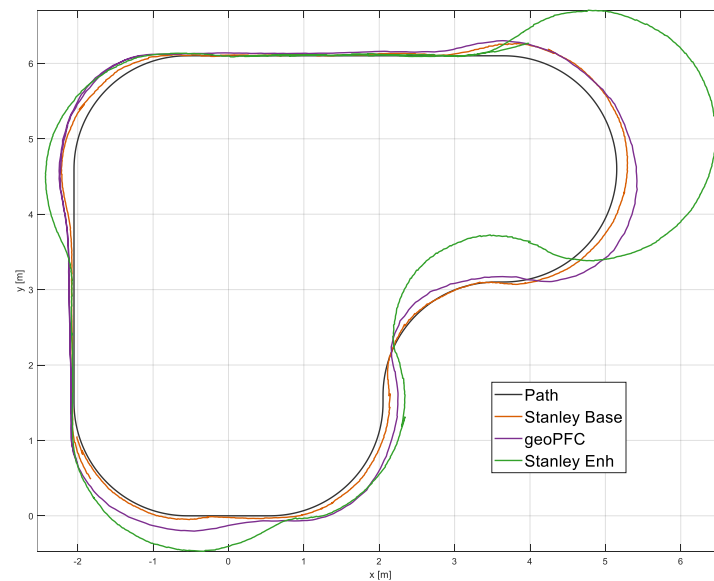


Figure 5.2: Controller Trajectories on the Race Track with Improved Parameter Set

Error Controller	e_{lat} RMSE	e_{lat} Max	e_{ψ} RMSE	e_{ψ} Max
Stanley Base	0.0764m	0.1837m	5.1°	19.0°
Stanley Enhance	0.5052m	1.3981m	18.9°	50.3°
geoPFC	0.1481m	0.3127m	5.51°	21.7°

Table 5.1.2: Error quantities for the evaluation on the vehicle with adapted Parameters

5.2 Evaluation

The first run showed that the simulation parameters transferred directly to the vehicle produce oscillation on both the Base Stanley and the enhanced Stanley. The geoPFC performed best because it was already tuned for the real vehicle.

The oscillation pattern from the first run look like the 100 ms latency simulation from Chapter 4.5.2. The same wiggling on straights, late correction in curves and overshoot at curve exits. This suggests the actual system delay on the miniAFM sits closer to 100 ms than the 50 ms assumed in simulation. Therefore, the gains were reduced as in chapter 4.5.2. In the second run the oscillation disappears for both Stanley controllers. The base Stanley improves significantly and outperforms the geoPFC with a lateral RMSE of 0.0764 m against 0.1481 m. The enhanced Stanley loses the oscillation, but the tracking gets worse. Its lateral RMSE rises from 0.4126 m to 0.5052 m and the heading errors grow as well. The reduced gains remove the oscillation but the controller drifts further outward through the curves.

The gap between simulation and real vehicle results from the enhanced Stanley likely comes from several sources. The parameters were tuned exclusively in simulation. The simulation model is a simplification that does not fully capture the real vehicle dynamics. On top of that the latency in simulation was set to 50 ms based on the SLAM clock rate. The actual delay on the vehicle is unknown but likely higher. The Stanley control law is also velocity dependent. This combination of model, latency and speed mismatch creates the sim-to-real gap. A dedicated parameter tuning on the real vehicle would be needed to find the right parameters for the enhanced Stanley.

6. Conclusion

This thesis implemented three different Stanley-based path following controllers and compared them to the existing geoPFC on the miniAFM. The path tracking performance is compared by various simulative testing scenarios.

The simulation results from chapter 4 show that across all of them the predictive Stanley achieves the best tracking performance followed by the base Stanley. Both outperform the geoPFC in tracking accuracy along all scenarios. The enhanced Stanley performs only on the race track better but could demonstrate its delay compensation for higher latencies and extend the gap on the geoPFC. The geoPFC assumes zero slip for the geometric control allocation. For the used maximum reference velocity in this thesis the assumption is not yet fully violated but a steady state offset is already observable on the U-Turn test. At higher velocities the slip will increase and the geoPFC will likely not be able to compensate the lateral error correctly. The Stanley-based controllers implemented in this thesis include a dynamic term that accounts for slip. This makes them more suitable for future operation at higher velocities.

On the real vehicle only the base and enhanced Stanley could be compared to the geoPFC. Due to time constraints two test runs with different parameter sets were performed but no dedicated tuning on the real platform was possible. The first run with simulation parameters produced oscillation on both Stanley controllers. After reducing the parameters, the oscillation disappeared. The base Stanley improved and outperformed the geoPFC. The enhanced Stanley lost the oscillation, but the tracking got worse with reduced gains. The oscillation pattern from the first run matches the 100 ms latency simulation from Chapter 4, suggesting the actual system delay is higher than the assumed 50 ms.

All three implemented controllers outperform the currently existing geoPFC on the race track in simulation. Thus, they are promising controllers to replace the geoPFC on the miniAFM. Whether the enhanced Stanley performs better than the base Stanley cannot be stated clearly. The latency tests indicate that parameter optimization is necessary to compare both controllers properly.

Outlook

The long-term goal for the miniAFM is to drive the race track at significantly higher speeds than the current maximum of $2 \frac{m}{s}$. To achieve this several steps are planned.

First, wheel speed sensors need to be installed on the front axle. The Predictive Stanley requires front wheel rotational velocities as input for its prediction model. Currently only

the rear wheels are equipped with Hall sensors, which means the best-performing controller from simulation cannot be tested on the real vehicle yet.

Second, the exact system latency must be measured. The simulation assumed 50 ms based on the SLAM clock rate but the real vehicle behaviour suggests the actual delay is higher. Knowing the true delay would reduce the sim-to-real gap and lower the effort needed for parameter re-tuning on the vehicle.

Third, the simulation model from Chapter 2.1.2 needs improvement at higher velocities. A more accurate vehicle model would make the simulation results more transferable and improve the prediction model used in the Predictive Stanley.

A further possible improvement is the implementation of a fuzzy supervisor that adapts the prediction horizon length and weighting parameters online based on the current velocity and tracking error. This would reduce the manual tuning effort and improve robustness across different operating conditions [Abd23].

References

- [Abd20] Abdelmoniem, A., Osama, A., Abdelaziz, M., & Maged, S. A. (2020). A Path-Tracking Algorithm Using Predictive Stanley Lateral Controller. *International Journal of Advanced Robotic Systems*, 17(6), 1–11.
- [Abd23] Abdelmoniem, A., Ali, A., Taher, Y., Abdelaziz, M., & Maged, S. A. (2023). Fuzzy Predictive Stanley Lateral Controller with Adaptive Prediction Horizon. *Measurement and Control*, 56(9–10), 1510–1522.
- [Ame17] Amer, N. H., Zamzuri, H., Hudha, K., & Kadir, Z. A. (2017). Modelling and Control Strategies in Path Tracking Control for Autonomous Ground Vehicles: A Review of State of the Art and Challenges. *Journal of Intelligent & Robotic Systems*, 86(2), 225–254.
- [Bad19] Badue, C., Guidolini, R., Carneiro, R. V., Azevedo, P., Cardoso, V. B., Forechi, A., Jesus, L., Berriel, R., Paixão, T. M., Mutz, F., Veronese, L., Oliveira-Santos, T., & De Souza, A. F. (2019). Self-Driving Cars: A Survey. *Expert Systems with Applications*, 165, 113816.
- [Bre25] Brembeck, J., de Castro, R., Ultsch, J., Tobolar, J., Winter, C., & Ahmic, K. (2025). VDCWorkbench: A Vehicle Dynamics Control Test & Evaluation Library for Model and AI-based Control Approaches. *Proceedings of the 16th International Modelica Conference*. Lucerne, Switzerland: The Modelica Association.
- [Bue11] Bünte, T., Brembeck, J., & Ho, L. M. (2011). Human Machine Interface Concept for Interactive Motion Control of a Highly Maneuverable Robotic Vehicle. *Proceedings of the IEEE Intelligent Vehicles Symposium* (pp. 1170–1175). Baden-Baden, Germany: IEEE.
- [Cho20] D. Choi, "Development of Open-Source Motor Controller Framework for Robotic Applications," in *IEEE Access*, vol. 8, pp. 14134–14145, 2020, doi: 10.1109/ACCESS.2020.2965977
- [Cou92] Coulter, Craig. "Implementation of the Pure Pursuit Path Tracking Algorithm." (1992).
- [DBLB10] Daniel, J., Birouche, A., Lauffenburger, J.-P., & Basset, M. (2010). Energy Constrained Trajectory Generation for ADAS. In *IEEE Intelligent Vehicles Symposium (IV)* (pp. 244–249).
- [Fal07] Falcone, Paolo, Francesco Borrelli, Jahan Asgari, H. Eric Tseng and Davor Hrovat. "Predictive Active Steering Control for Autonomous Vehicle Systems." *IEEE Transactions on Control Systems Technology* 15 (2007): 566–580.

- [Hof07] Hoffmann, G., Claire J. Tomlin, Michael Montemerlo and Sebastian Thrun. "Autonomous Automobile Trajectory Tracking for Off-Road Driving: Controller Design, Experimental Validation and Racing." *2007 American Control Conference* (2007): 2296-2301.
- [Keb23] Kebbati, Y., Ait-Oufroukh, N., Ichalal, D., & Vigneron, V. (2023). Lateral Control for Autonomous Wheeled Vehicles: A Technical Review. *Asian Journal of Control*, 25(4), 2539–2563.
- [Koi24] Koide, K., Yokozuka, M., Oishi, S., & Banno, A. (2024). GLIM: 3D Range-Inertial Localization and Mapping with GPU-Accelerated Scan Matching Factors. *Robotics and Autonomous Systems*, 179, 104750.
- [Pas08] M. Pascal and S. Claude, "Motion Control of Wheeled Mobile Robots," in *Handbook of Robotics*, K. Siciliano, Ed., Springer, 2008, pp. 799-826.
- [Oke20] O’Kelly, M., Zheng, H., Karthik, D., & Mangharam, R. (2021). F1TENTH: An Open-Source Evaluation Environment for Continuous Control and Reinforcement Learning. *Proceedings of Machine Learning Research*, 123, 77–89.
- [Pad16] Paden, B., Čap, M., Yong, S. Z., Yershov, D., & Frazzoli, E. (2016). A Survey of Motion Planning and Control Techniques for Self-Driving Urban Vehicles. *IEEE Transactions on Intelligent Vehicles*, 1(1), 33–55
- [Pol17] Polack, P., Altché, F., d’Andréa-Novel, B., & de La Fortelle, A. (2017). The Kinematic Bicycle Model: A Consistent Model for Planning Feasible Trajectories for Autonomous Vehicles? *Proceedings of the IEEE Intelligent Vehicles Symposium* (pp. 812–818). Los Angeles, USA: IEEE.
- [Rit15] Ritzer, P., Winter, C., & Brembeck, J. (2015). Advanced Path Following Control of an Overactuated Robotic Vehicle. *Proceedings of the IEEE Intelligent Vehicles Symposium* (pp. 1120–1125). Seoul, South Korea: IEEE.
- [Rit16] Ritzer, P., Winter, C., & Brembeck, J. (2016). Experimental Validation of Geometric Path Following Control with Demand Supervision on an Over-Actuated Robotic Vehicle. *Proceedings of the IEEE Intelligent Vehicles Symposium* (pp. 539–545). Gothenburg, Sweden: IEEE.
- [Pen21] Chen, Pengcheng. (2021). SURFACE VEHICLE RECOMMENDED PRACTICE (R) Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles.

- [Sam94] Sampei, M. (1994). A Control Strategy for a Class of Nonholonomic Systems – Time-State Control Form and its Application. *Proceedings of the 33rd IEEE Conference on Decision and Control* (pp. 1120–1121). Lake Buena Vista, FL, USA: IEEE.
- [Sei23] Seiffer, Alexander & Frey, Michael & Gauterin, Frank. (2023). Pragmatic and Effective Enhancements for Stanley Path-Tracking Controller by Considering System Delay. *Vehicles*, 5(2), 615–636.
- [Sni09] Snider, J. M. (2009). Automatic Steering Methods for Autonomous Automobile Path Tracking. Technical Report CMU-RI-TR-09-08, Robotics Institute, Carnegie Mellon University, Pittsburgh, PA.
- [Sta23] Stano, P., Montanaro, U., Tavernini, D., Tufo, M., Fiengo, G., Novella, L., & Sorniotti, A. (2023). Model Predictive Path Tracking Control for Automated Road Vehicles: A Review. *Annual Reviews in Control*, 55, 194–236.

Danksagung

An dieser Stelle möchte ich mich herzlich bei allen Personen bedanken, die mich während der Bearbeitung dieser Arbeit unterstützt haben.

Mein Dank gilt Prof. Dr.-Ing. Hans-Georg Herzog, Leiter der Professur für Energiewandlungstechnik an der Technischen Universität München, und Dr.-Ing. Jonathan Brembeck, Leiter der Abteilung Fahrzeug-Systemdynamik und Regelungstechnik am Institut für Fahrzeugkonzepte des DLR, für die Möglichkeit zur Durchführung dieser Bachelorarbeit.

Mein besonderer Dank gilt meinem Betreuer Johannes Rein für seine kontinuierliche Unterstützung sowie sein stets hilfreiches Feedback während der gesamten Bearbeitungszeit. Durch seine Geduld und seine Bereitschaft, sich Zeit für Fragen und Anregungen zu nehmen, hat er maßgeblich zum Gelingen dieser Arbeit beigetragen.

Nicht zuletzt möchte ich mich für das angenehme und inspirierende Arbeitsumfeld bedanken, das die Durchführung der Simulationen und Versuche auf der Versuchsplattform ermöglicht hat.

Vincent Sperr

A. Appendix

A.1. Simulation Model Parameter

Parameter	Symbol	Value
Vehicle mass	m	7.151 kg
Distance CoG to front axle	l_f	0.1805 m
Distance CoG to rear axle	l_r	0.1805 m
Track width	w	0.265 m
Wheel radius	r_w	0.0525 m
Friction coefficient	μ	0.16
Jaw Inertia	J_ψ	$0.1195 \text{ kg} \cdot \text{m}^2$

Table 5.2.1: Simulation Model Parameters for the miniAFM

A.2. Parameters for Testing scenarios

Parameter	geoPFC	Base Stanley	Pred. Stanley	Enh. Stanley
λ_{elat}	0.2	--	--	--
λ_ψ	0.05	--	--	--
K	--	30	14	15
$K_{\text{prot}} (\frac{\text{m}}{\text{s}})$	--	0.1	0.1	0.1
$K_{d,\text{yaw}}$	--	0.12	0.05	0.12
$K_{d,\text{steer}}$	--	0	0	0
N	--	--	3	--
$T(\text{s})$	--	--	0.01	--

$K_{Weigh,k}$	--	--	[1,0.7,0.2,0.1]	--
$T_{ff}(s)$	--	--	--	0.1

Table 5.2.2: List of the Control Parameter Set for the U-Turn Scenario

Parameter	geoPFC	Base Stanley	Pred. Stanley	Enh. Stanley
λ_{elat}	0.18	--	--	--
λ_{ψ}	0.18	--	--	--
K	--	15	15	15
$K_{prot} (\frac{m}{s})$	--	0.1	0.1	0.1
$K_{d,yaw}$	--	0.05	0.05	0.05
$K_{d,steer}$	--	0	0	0
N	--	--	4	--
$T(s)$	--	--	0.01	--
$K_{Weigh,k}$	--	--	[1,0.3,0.2,0.1 ,0.05]	--
$T_{ff}(s)$	--	--	--	0.09

Table 5.2.3: List of the Control Parameter Set for the Double Bend Curve

Parameter	geoPFC	Base Stanley	Pred. Stanley	Enh. Stanley
λ_{elat}	0.85	--	--	--
λ_{ψ}	0.2	--	--	--
K	--	10	16	4
$K_{prot} (\frac{m}{s})$	--	0.1	0.1	0.1
$K_{d,yaw}$	--	0.14	0.11	0.03
$K_{d,steer}$	--	0	0	0
N	--	--	5	--
$T(s)$	--	--	0.01	--
$K_{Weigh,k}$	--	--	[0.6,0.2,0.1,0.1,0.05,0.02]	--

$T_{ff}(s)$	--	--	--	0.1
-------------	----	----	----	-----

Table 5.2.4: List of the Control Parameter Set for the race track

Parameter	geoPFC	Base Stanley	Enh. Stanley
λ_{elat}	0.5		
λ_{ψ}	1		
K	--	10	9
$K_{\text{prot}} (\frac{\text{m}}{\text{s}})$	--	0.1	0.1
$K_{d,yaw}$	--	0.1	0.1
$K_{d,steer}$	--	0	0
$T_{ff}(s)$	--	--	0.09

Table 5.2.5: List of the Control Parameter Set for the Test on the miniAFM

A.3. Improved Parameters

Parameter	geoPFC	Base Stanley	Pred. Stanley	Enh. Stanley
λ_{elat}	0.9	--	--	--
λ_{ψ}	0.5	--	--	--
K	--	4	7	4
$K_{\text{prot}} (\frac{\text{m}}{\text{s}})$	--	0.1	0.1	0.1
$K_{d,\text{yaw}}$	--	0.05	0.05	0.03
$K_{d,\text{steer}}$	--	0	0	0
N	--	--	4	--
$T(\text{s})$	--	--	0.01	--
$K_{\text{weigh},k}$	--	--	[1,0.15,0.1,0.1,0.05]	--
$T_{ff}(\text{s})$	--	--	--	0.1

Table 5.2.6: List of the Control Parameter set for the offset

Parameter	geoPFC	Base Stanley	Pred. Stanley	Enh. Stanley
λ_{elat}	2.9	--	--	--
λ_{ψ}	0.9	--	--	--
K	--	2.1	4	1.5
$K_{\text{prot}} (\frac{\text{m}}{\text{s}})$	--	0.1	0.1	0.1
$K_{d,\text{yaw}}$	--	0.15	0.15	0.1
$K_{d,\text{steer}}$	--	0	0	0
N	--	--	5	--
$T(\text{s})$	--	--	0.025	--
$K_{\text{weigh},k}$	--	--	[0.2,0.5,0.3,0.1,0.1,0.1]	--

$T_{ff}(s)$	--	--	--	0.19
-------------	----	----	----	------

Table 5.2.7: Parameter set used to improve tracking performance at 100ms delay.

Parameter	geoPFC	Base Stanley	Pred. Stanley	Enh. Stanley
λ_{elat}	3	--	--	--
λ_{ψ}	1.5	--	--	--
K	--	1	2	0.8
$K_{\text{prot}} (\frac{\text{m}}{\text{s}})$	--	0.1	0.1	0.1
$K_{d,yaw}$	--	0.2	0.16	0.2
$K_{d,steer}$	--	0	0	0
N	--	--	4	--
$T(s)$	--	--	0.03	--
$K_{\text{Weigh},k}$	--	--	[0.2,0.5,0.3,0.2,0.1,0.1]	--
$T_{ff}(s)$	--	--	--	0.25

Table 5.2.8: Improved Parameter Set for 150 ms delay

Parameter	geoPFC	Base Stanley	Enh. Stanley
λ_{elat}	0.5		
λ_{ψ}	1		
K	--	4	3
$K_{\text{prot}} (\frac{\text{m}}{\text{s}})$	--	0.1	0.1
$K_{d,yaw}$	--	0.1	0.1
$K_{d,steer}$	--	0	0
$T_{ff}(s)$	--	--	0.15

Table 5.2: Improved Parameter Set for the Test on the miniAFM

Disclaimer

I hereby declare that this thesis is entirely the result of my own work except where other-wise indicated. I have only used the resources given in the list of references. For translation purposes, the company-internal version of DeepL was used. The author assumes full responsibility for the accuracy and correctness of the translated content.

This thesis has not been submitted in the same or a similar form to any other examination authority.

Munich, 06.04.26



Sperr Vincent