Autonomous Car Modeling and Control summary

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Artificial Intelligence & Information Analysis Lab

Autonomous Car Modeling and Control

- **Introduction**
- Dynamic Models
  - Car-Body Dynamics – The Slow Dynamics
  - Tire Dynamics – The Fast Dynamics
- Kinematic Models
  - System Equations
  - Bicycle – Car Kinematic Model
- Point – Mass Models
- Autonomous Vehicle Control Techniques
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- Deep Autonomous Vehicle Control

Introduction

Vehicle models depending on their dynamics can be classified into three major categories that we will develop below:

- **Dynamic Models**
- **Kinematic Models**
- **Point – Mass Models**

Introduction

- ***Dynamic Models***

These models essentially describe the relationship that the vehicle has with the road. The complexity of these models results from the non - linearity of the relationships between the tires and the other parts of the vehicle.

Introduction

- ***Kinematic Models***

These models consist a structure of equations that describe the geometry of the vehicle, representing the behavior of the vehicle in motion and during maneuvers.

Introduction

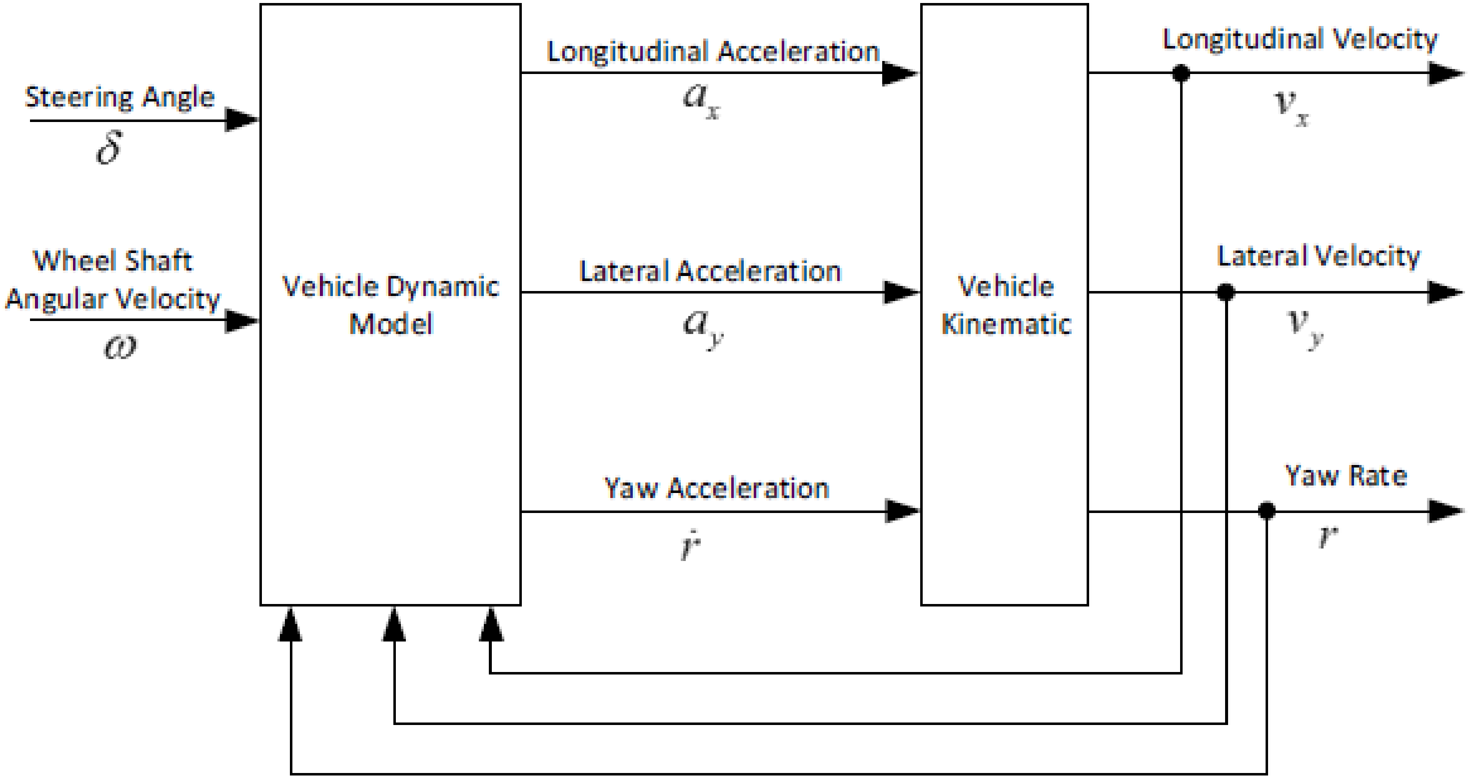

Figure 1: Diagram of Dynamic and Kinematic Model for Autonomous Driving [TM15].

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Dynamic Models

- To describe the car dynamics will be used three different frames:

- ***Inertial Frame***: it is described as $(\mathbf{e}_X, \mathbf{e}_Y, \mathbf{e}_Z)$
- ***Vehicle Frame***: it is described as $(\mathbf{e}_x, \mathbf{e}_y, \mathbf{e}_z)$
- ***Pneumatic or Tire Frame***: it is described as $(\mathbf{p}_{xi}, \mathbf{p}_{yi}, \mathbf{p}_{zi})$ where the i is associated with the wheel of the vehicle $i = 1, \ldots, 4$

Dynamic Models

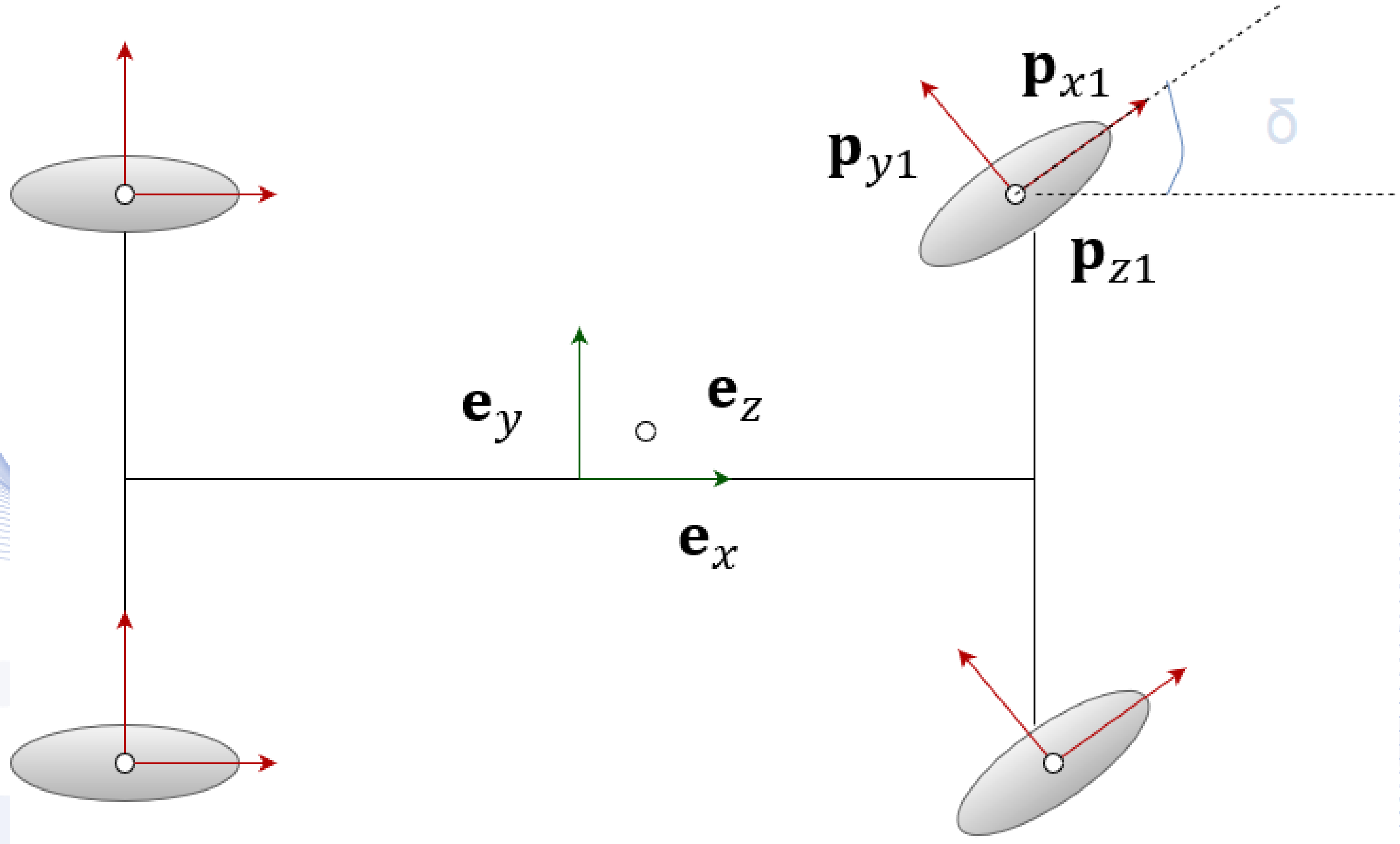

Figure 2: The Vehicle – Tire frame of a four wheel car.

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Car – Body Dynamics

- The slow dynamics, incluse six different variables, namely the ***longitudinal*** V_x, ***lateral*** V_y and ***vertical*** V_z velocities and the ***roll*** $\dot{\theta}$, ***pitch*** $\dot{\varphi}$ and ***yaw*** $\dot{\psi}$ angular velocities.

- The model inputs are the longitudinal and lateral forces F_{xi} and F_{yi} applied by the road on the different wheels i in the vehicle frame (or equivalently F_{xpi} and F_{ypi} in the pneumatic frame). This concept shown in Figure 3.

Car – Body Dynamics

In the following Figure we see the Dynamics of a car which moves in a hill. We must describe the F_{aero}, which consist the air force that hits the car.

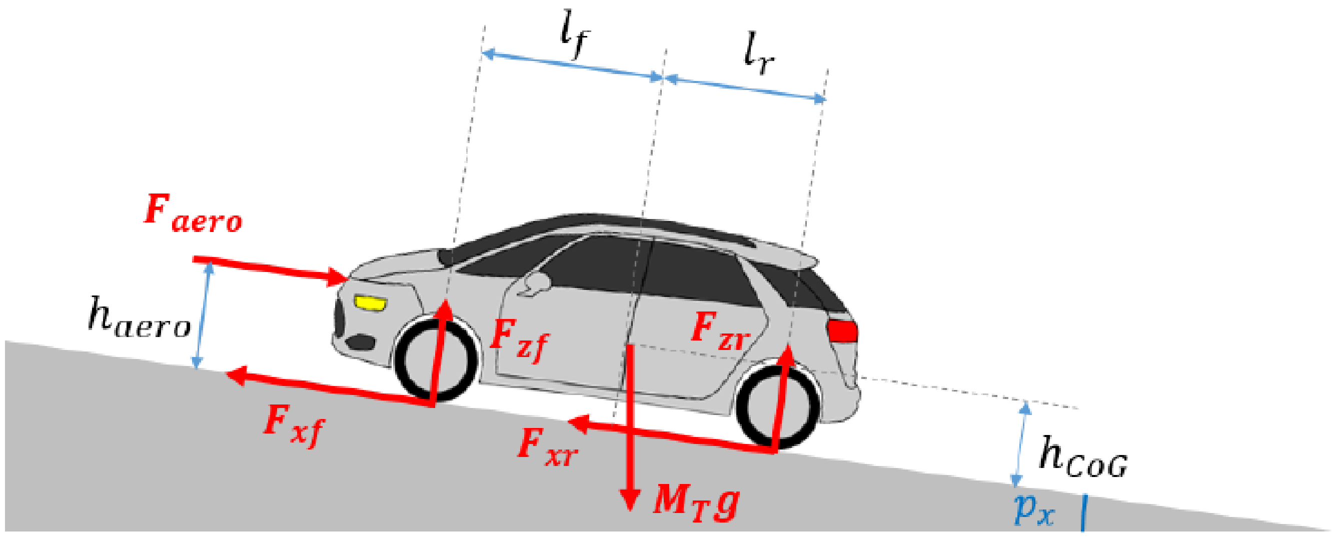

Figure 4: Applied Forces in a car [POL18].

Car – Body Dynamics

Here we will describe the four-wheel vehicle model dynamics. Compared to the dynamic bicycle model, the slope and road-bank angle are defined, as well as the roll, pitch and vertical motions.

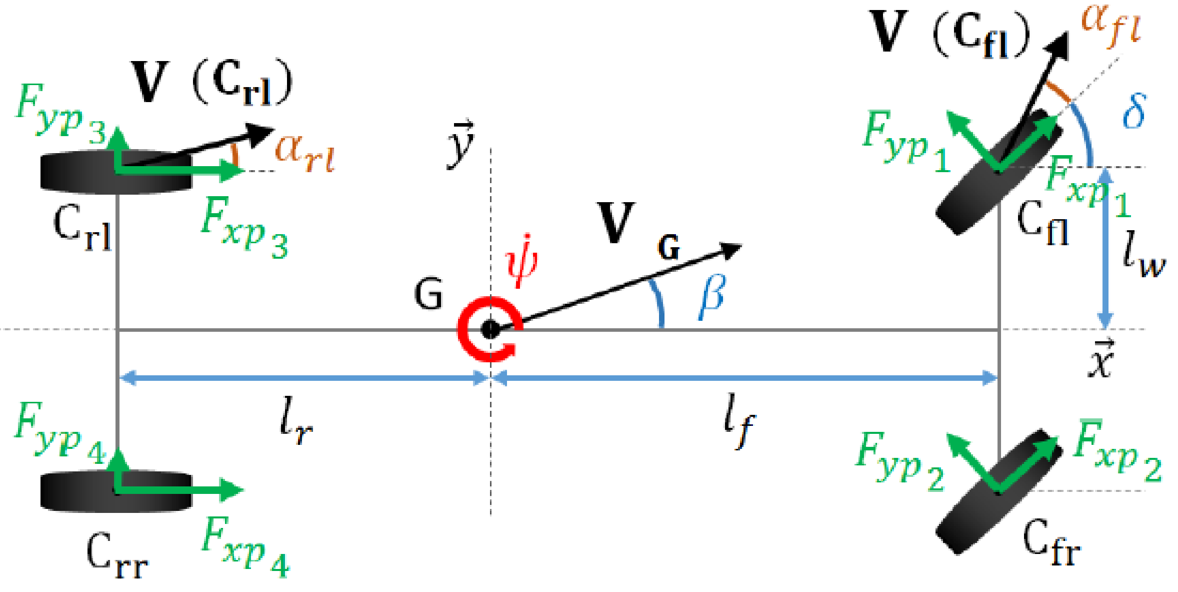

Figure 5: Four - Wheel Dynamic Model [POL18].

Car – Body Dynamics

The suspension force variation F_{s1} applied at wheel i depends on the variation of the length of the suspension $\Delta z_{s1} = z_{si} - z_{ti}$.

The normal reaction F_{zi} force applied by the road on wheel i is given by the following Equations. The P_r is the weight of the wheel as shown in Figure 6.

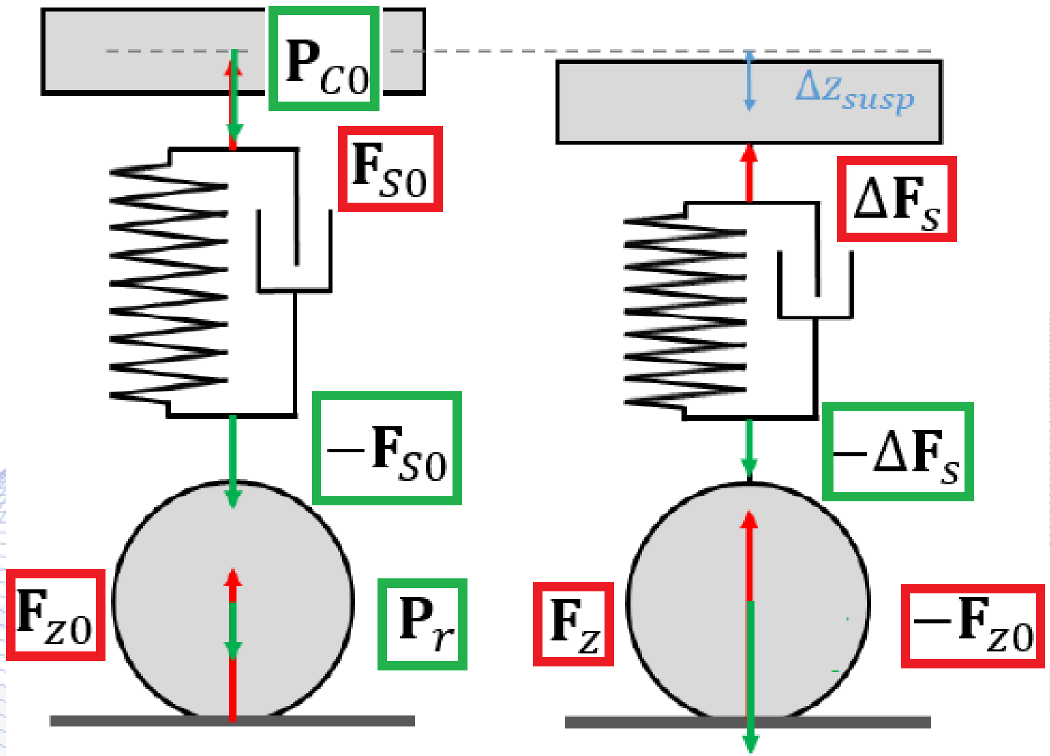

Figure 6: The Wheel Dynamics.

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Tire Dynamics

The ***longitudinal*** F_{xp} and ***lateral*** F_{yp} forces of tires are not given directly from the driver.

That is why we must describe the steering wheel actions. The tire forces generated by the gas pedal and the brake pedal.

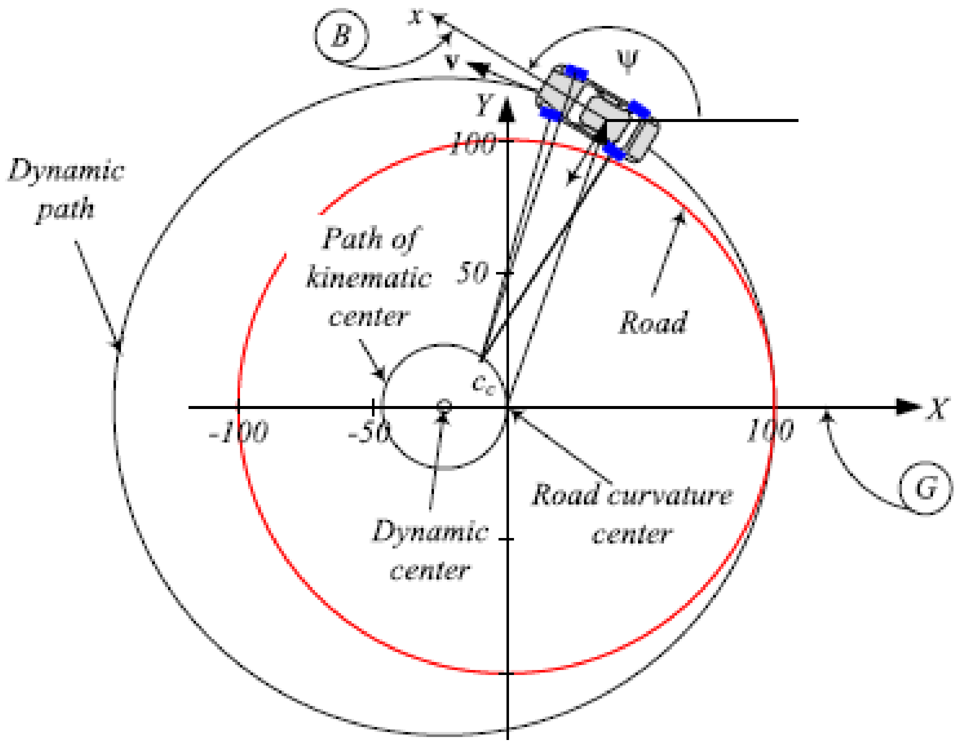

Figure 7: Dynamics of an understeer vehicle [MKT19].

Tire Dynamics

The ***longitudinal*** F_{xp} and ***lateral*** F_{yp} forces generated by the road on each tire expressed in the pneumatic frame are obtained from the following four variables:

- The longitudinal slip ratio: τ_x
- The lateral slip angle: α
- The normal reaction force of the road on the wheel: F_z
- The road friction coefficient: μ

Tire Dynamics

Figure 8: The main concept of the tire dynamics.

The ***Tire model*** can be expressed from the following Equations:

$$F_{xp} = f_x(\tau_x, \alpha, F_z, \mu)$$

$$F_{yp} = f_x(\alpha, \tau_x, F_z, \mu)$$

Tire Dynamics

The first Equation refers to the ***Traction*** phase while the second Equation refers to the ***Braking*** phase.

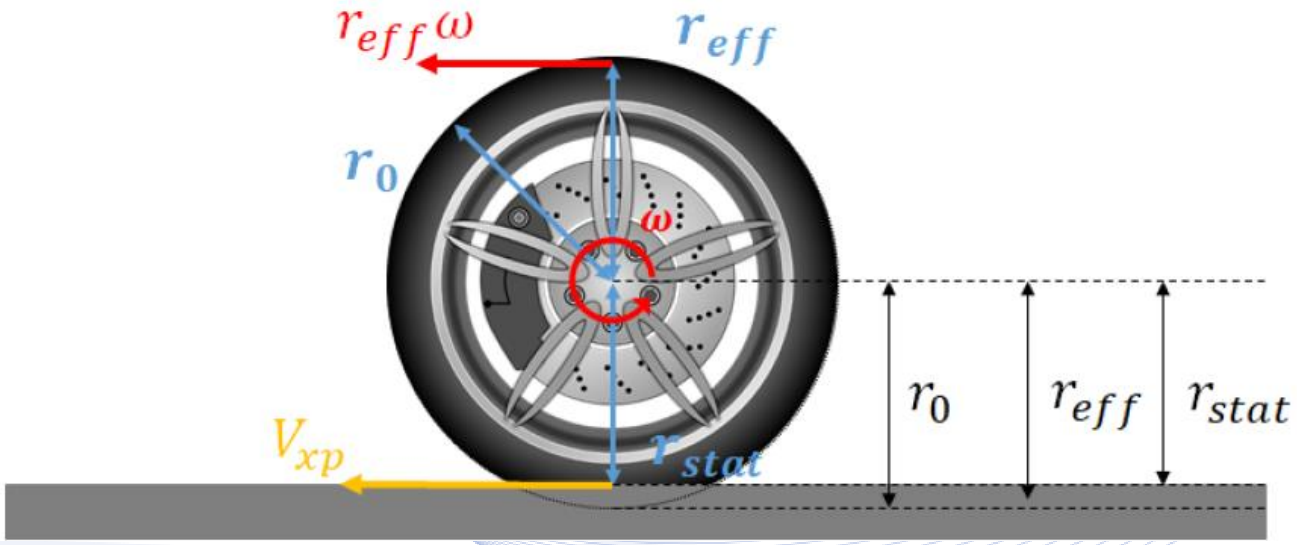

Figure 9: Forces on the Tire Dynamic Model [POL18].

$$\tau_{xi} = \frac{r_{eff}\omega_i - V_{xpi}}{r_{eff}|\omega_i|}, r_{eff}\omega_i \geq V_{xpi}$$

$$\tau_{xi} = \frac{r_{eff}\omega_i - V_{xpi}}{V_{xpi}}, r_{eff}\omega_i \leq V_{xpi}$$

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Tire Dynamics

Now, we must describe the ***lateral slip angle*** a_i

It is the wheel's orientation vector i and the velocity vector of the same wheel as shown in Figure 10.

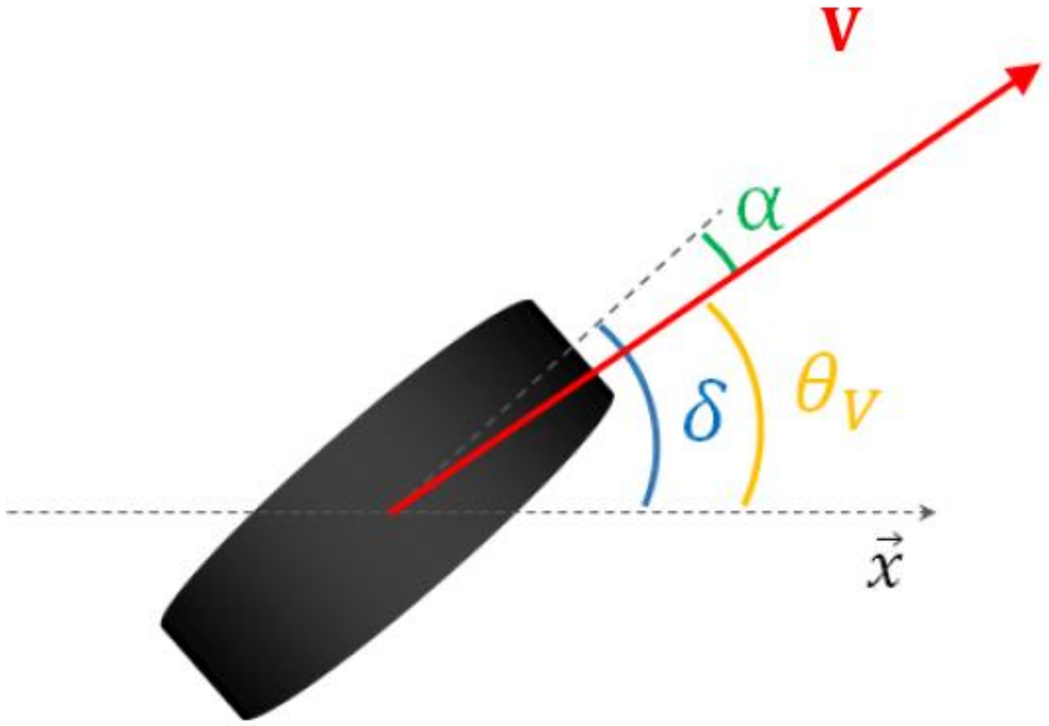

Figure 10: Later slip angle on the Tire Dynamic Model [POL18].

Tire Dynamics

The first Equation refers to the front wheels while the second Equation refers to the rear wheels.

$$\alpha_i = \delta_f - \operatorname{atan}\left(\frac{V_y + l_f\,\dot{y}}{V_x + \epsilon l_w\,\dot{y}}\right)$$

$$\alpha_i = -\operatorname{atan}\left(\frac{V_y + l_r\,\dot{y}}{V_x + \epsilon l_w\,\dot{y}}\right)$$

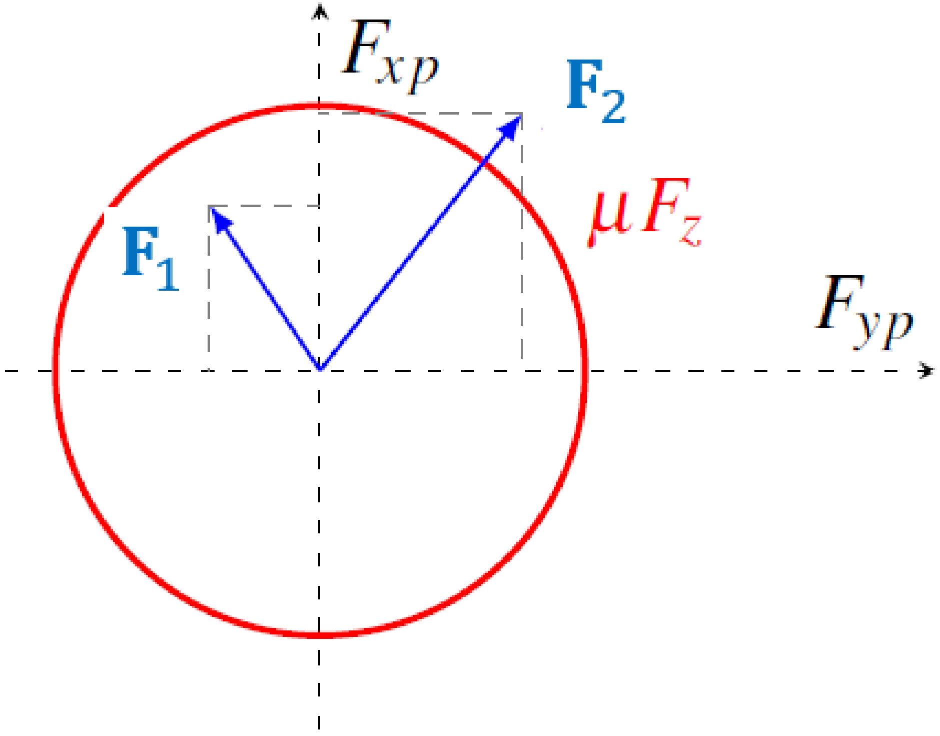

Figure 11: The Friction circle.

Tire Dynamics

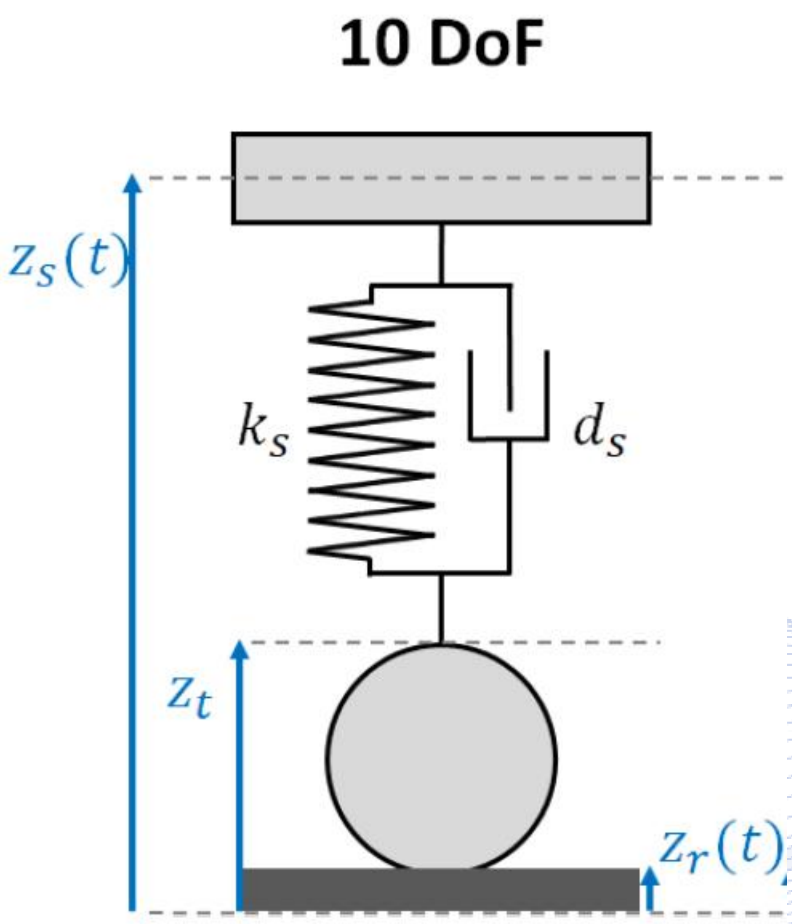

Figure 12: The proposed model vehicle model [POL18].

Finally, the combination of the f principles of the ***car – body dynamics*** with a ***tire model*** we get a 10 Degrees of Freedom vehicle model (10 DoF).

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Kinematic Models

The Equations for this model are simpler. The kinematic vehicle model assumes that no slip occurs between the ground and the wheels, which is accurate for vehicles moving at low speeds.

In this case, the velocity directions at points F and R (V_F and V_R) are consistent with the directions of the front and rear wheels

Kinematic Models

$$\dot{X} = V_G \cos(\psi + \beta)$$

$$\dot{Y} = V_G \sin(\psi + \beta)$$

$$\dot{\psi} = V_G \cos(\beta) \tan(\delta) / (l_f + l_r)$$

$$\dot{V}_G = \alpha$$

$$\beta = \tan^{-1}(\frac{l_r}{l_f + l_r} \tan(\delta))$$

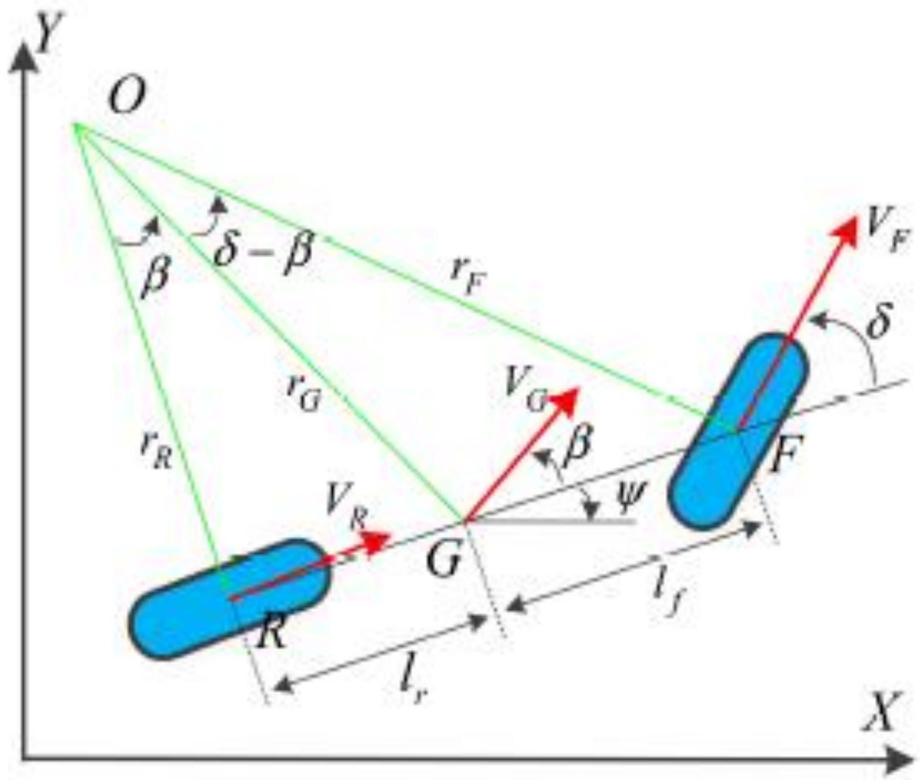

Figure 13: Diagram of the four wheel Kinematic model [MWCZ19].

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Bicycle – Car Kinematic Model

Because the bicycle model is often mentioned in the literature, efforts have been made to form the basis for the study and development of corresponding car models.

In the picture below we see how a bicycle model can be adapted to a kinematic vehicle model with four wheels.

Bicycle – Car Kinematic Model

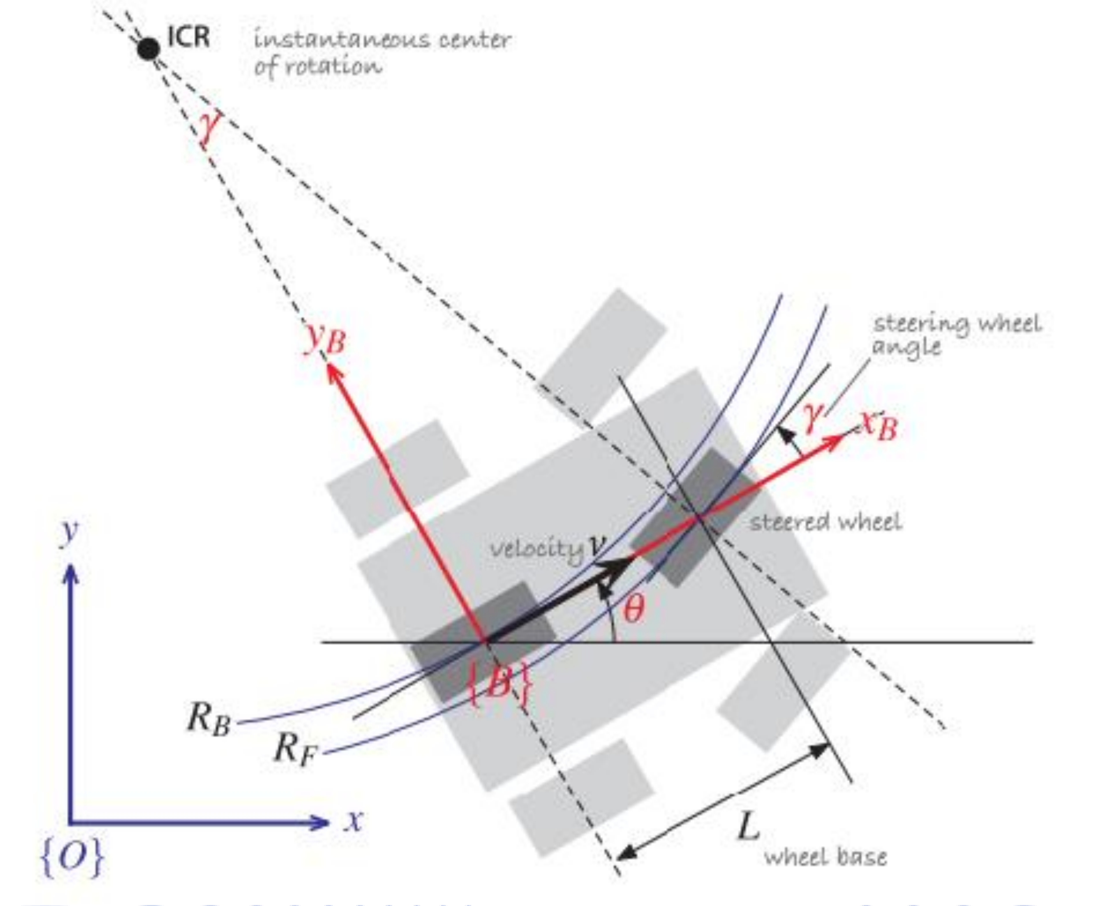

Figure 14: Bicycle model of a four wheel car [YEO20].

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Point – Mass Models

As we described in the Introduction the ***Point - Mass*** models are the simplest models of a vehicle.

The latter is assimilated to a point - mass where the ***control inputs*** are good enough for a second order point - mass model. The accelerations in the inertial frame are the a_X and a_Y.

Point – Mass Models

The most important is that the system obtained is a linear one.

$$\dot{\xi}_{pm} = \mathbf{A}\xi_{pm} + \mathbf{B}U_{pm}$$

The second order point - mass model can described from $p_m = (X, \dot{X}, Y, \dot{Y})^T$ which is the state of the vehicle and $U_{pm} = (X, Y)^T$ which is the control input. The $\mathbf{A}$ and $\mathbf{B}$ are diagonal 4×4 and 2×2 matrices, respectively. The variables X and Y describe the ***positions*** of the vehicle in the inertial frame while the $\dot{X}$ and $\dot{Y}$ describe the ***speed*** of the vehicle in the inertial frame.

Point – Mass Models

As shown in Figure 15 the vehicle can move in many directions, this idea makes the model ***week*** and ***poor*** in accuracy. If we want to avoid pure lateral motion, we assume the following Equation.

$$|\dot{Y}| \leq k|\dot{X}|$$

where,

$$0 < \tan(\psi_{max}) < 1$$

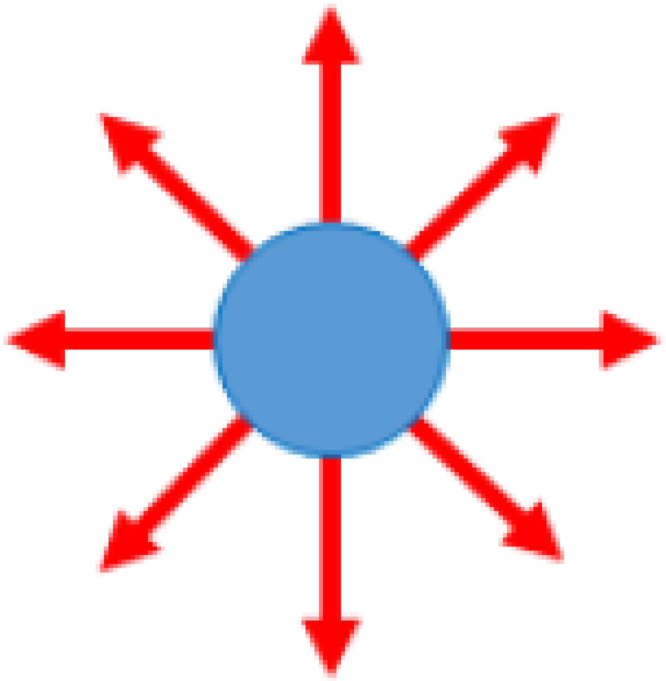

Figure 15: The proposed Point - Mass model [POL18].

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Autonomous Vehicle Control

In order to execute the reference path or trajectory from the motion planning system a ***feedback controller*** is used to select appropriate actuator inputs to carry out the planned motion and correct tracking errors.

The tracking errors generated during the execution of a planned motion are due in part to the inaccuracies of the vehicle model.

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Model Predictive Control Law

The ***Model Predictive Control*** (MPC) model consist of a general and common methodology for autonomous vehicles control. The MPC method solves the motion planning problem over a short time horizon, by taking a short interval of the resulting open loop control and apply it to the system.

The model takes the form of a general continuous time control system with control, $u(t) \in \mathbb{R}^m$ and the state, $x(t) \in \mathbb{R}^n$.

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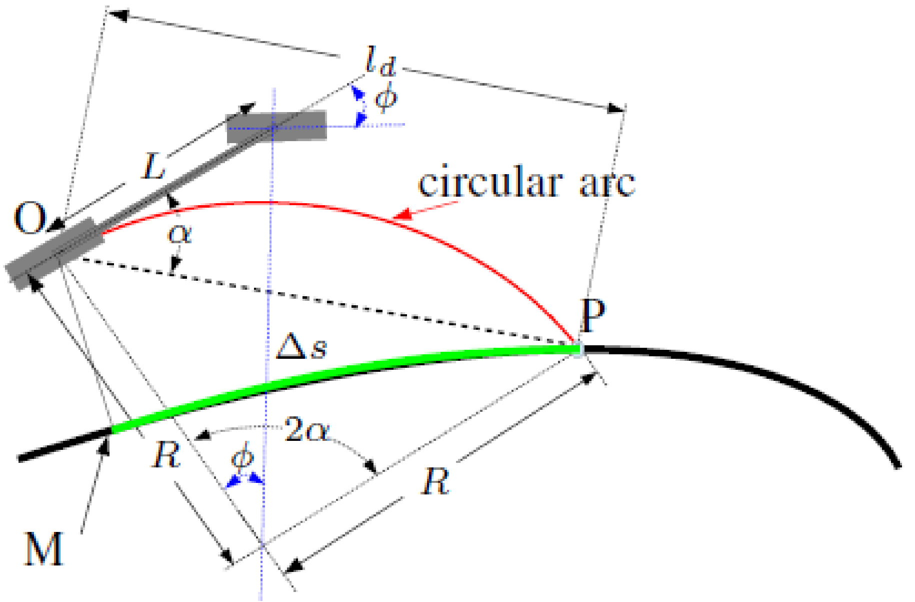
Pure Pursuit Control Law

The pure pursuit is a lateral control strategy. In this control law, a goal point is defined on the desired path, by looking ahead distance l_d from the current position of the rear axle center O to the desired path.

Then the curvature of the arc that connects O to the goal point is calculated geometrically.

Pure Pursuit Control Law

The required steering angle is calculated from the following Equation:



$$\frac{l_d}{\sin(2\alpha)} = \frac{R}{\sin(\frac{\pi}{2} - \alpha)} \Rightarrow \frac{l_d}{\sin(\alpha)} = 2R$$

Figure 16: The concept of the Pure Pursuit Law [DAGM16].

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Stanley Control Law

This Law was first introduced in Stanford University and won the DARPA Grand Challenge.

$$\phi(t) = \theta_p(t) + \tan^{-1}(\frac{d_f(t)}{l_d})$$

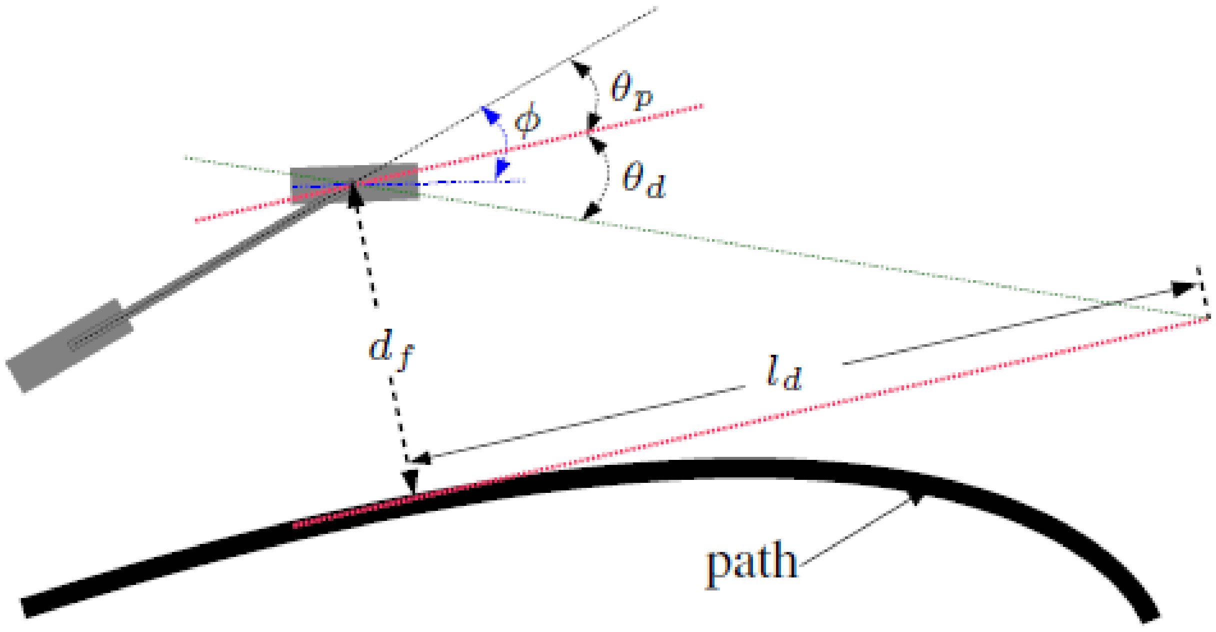

Figure 17: The Stanley Control Law [DAGM16].

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Modified Sliding Control Law

The sliding mode is a robust control model and does not require a precise model of the system and can also ensure stability. The sliding surface can be defined as following:

$$\psi = k_{\theta p}\theta_p + k_d d_r$$

where the k_p and k_d are weighting coefficients. The sliding mode controller assumes that:

$$\dot{\psi} = -K_\psi sign(\psi)$$

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Kinematic Lateral Speed Control Law

The new ***kinematic*** lateral speed control designed to control the rear lateral distance and the orientation error by controlling the lateral speed d_r, which in turn is controlled by the angular speed of the car $\dot{\theta}$ through the steering angle ϕ.

As the lateral speed d_r is under control, the motions toward the path are smoother, after tuning the parameters.

Kinematic Lateral Speed Control Law

If the car is far away from the road line, it must get closer at higher speed than if it is near, so the desired lateral speed $\hat{\dot{d}}_r$ can be defined as proportional to the lateral error d_r, with negative sign.

$$\hat{\dot{d}}_r = -k_{lat} d_r$$

The absolute value of the desired lateral speed is limited to a reasonable maximum value, which in our case is 1 m/s.

Kinematic Lateral Speed Control Law

The derivative of the lateral speed of the rear axle d_r is defined from the following Equation:

$$\dot{d}_r = v_u \sin(\theta_p)$$

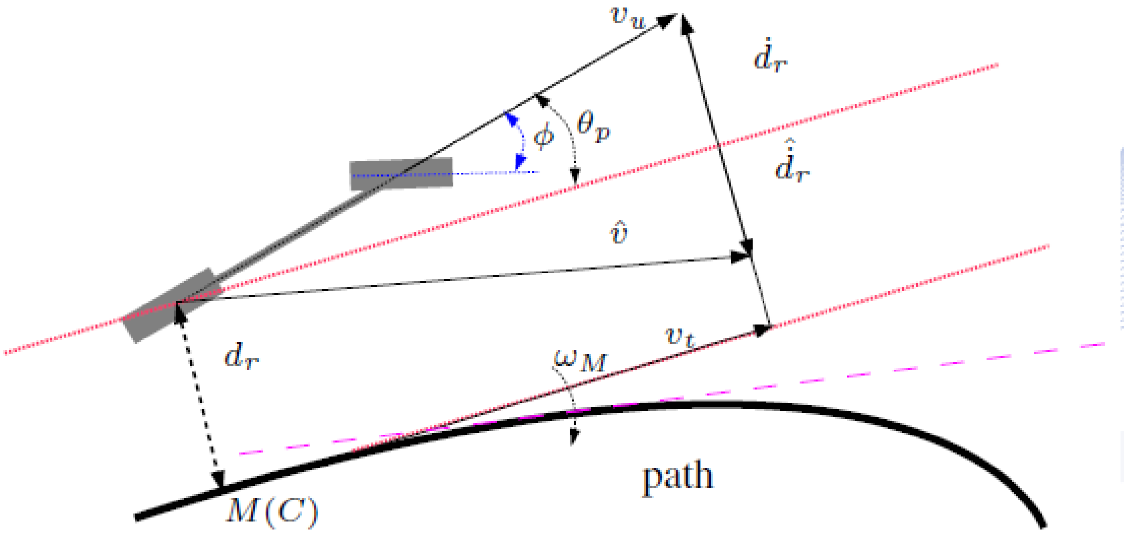

Figure 18: The Kinematic Lateral Control Law [DAGM16].

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Deep Autonomous Vehicle Control

Deep Learning models contribute to perception and to the processing of the sensory data in order to make informed decisions. The popular deep learning models used in autonomous car technology include:

- End – to end Learning
- Fully Convolutional Network
- Deep Reinforcement Learning
- CNN and Deep CNN
- Deep Boltzmann Machines
- Deep Autoencoders

Deep Autonomous Vehicle Control

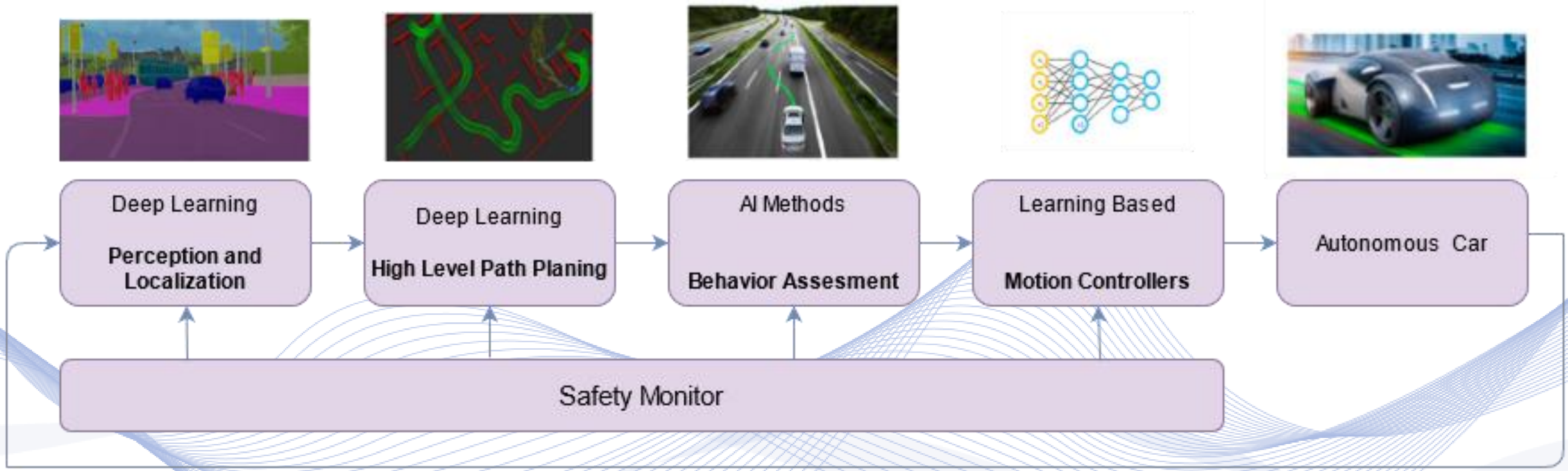

Figure 19: Block diagram of and AI powered Autonomous Car.

Deep Autonomous Vehicle Control

The DNN takes as inputs the information coming from ***Cameras***, ***LiDAR*** and ***IR Sensors***.

The outputs are important information for the control of the autonomous system and concern the ***Steering angle***, ***Brake*** and ***Acceleration***.

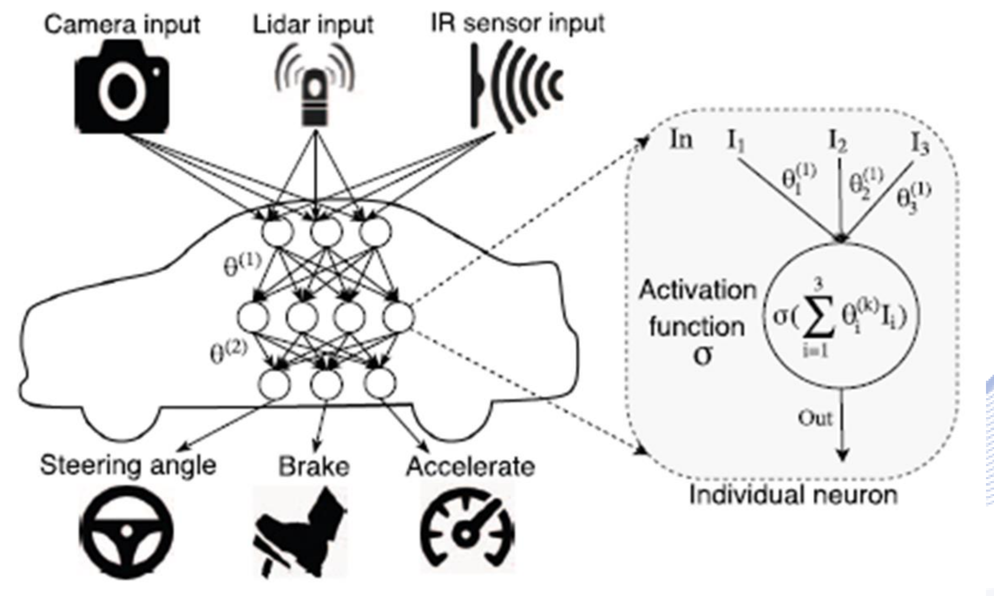

Figure 20: A simple autonomous car DNN [TPJR18].

Deep Autonomous Vehicle Control

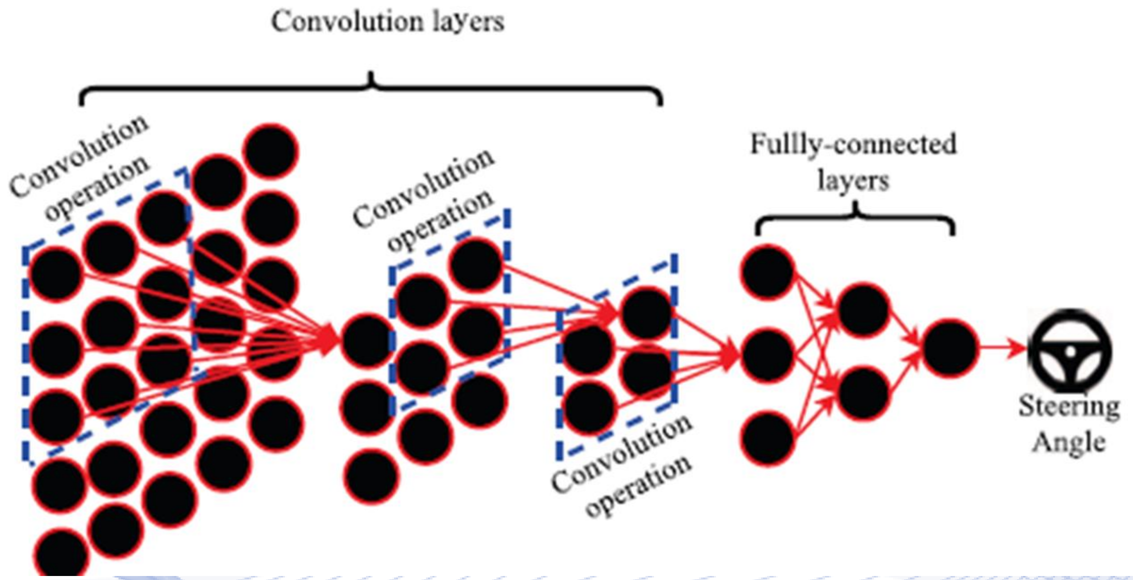

Figure 21: CNN architecture for Autonomous Driving Control [TPJR18].

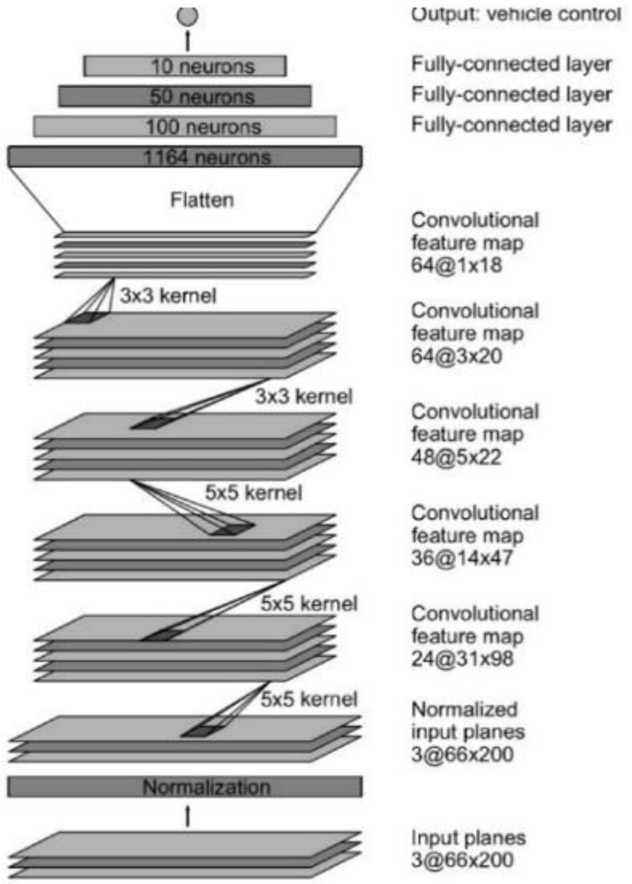

Figure 22: Nvidia proposed CNN architecture for Deep Autonomous Control.

Deep Autonomous Vehicle Control

The unrolled version on the right of Figure shows how the loop allows a sequence of inputs (images) to be fed to the ***RNN*** and the steering angle is predicted based on all those images. Specifically, the output of each layer is fed to the following layer and flow back to the previous layer.

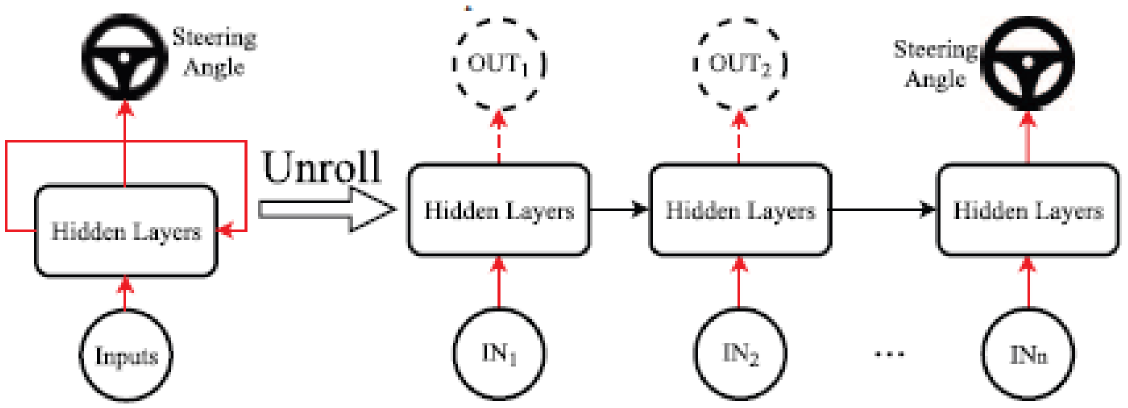

Figure 23: RNN architecture with loops for Autonomous Driving [TPJR18].

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