Advanced Programming Practice

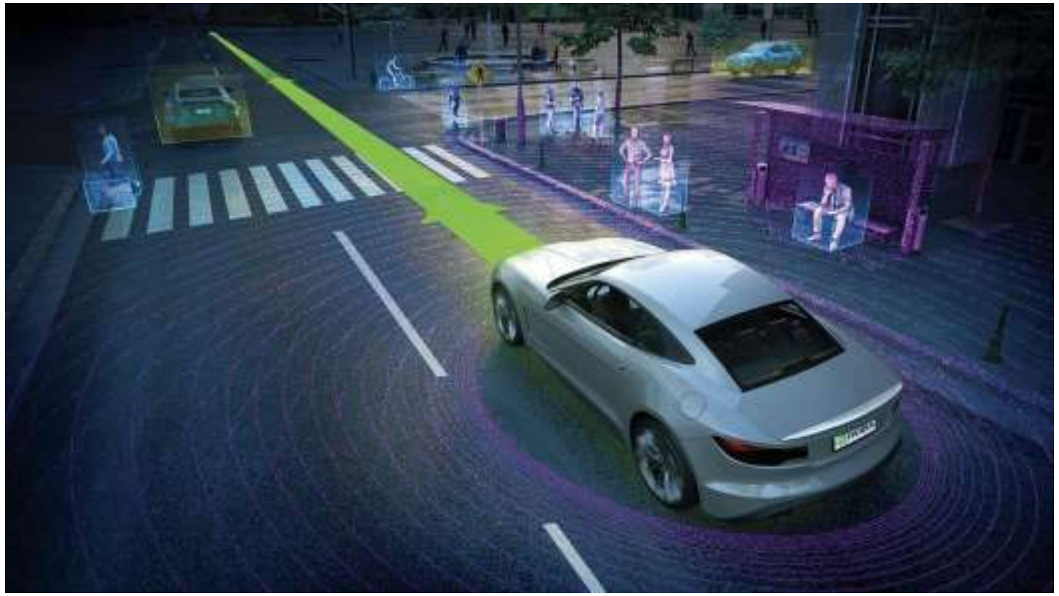
Autonomous Driving
-Lane detection-

2022 Fall

Sogang University

자율 주행(Autonomous driving)

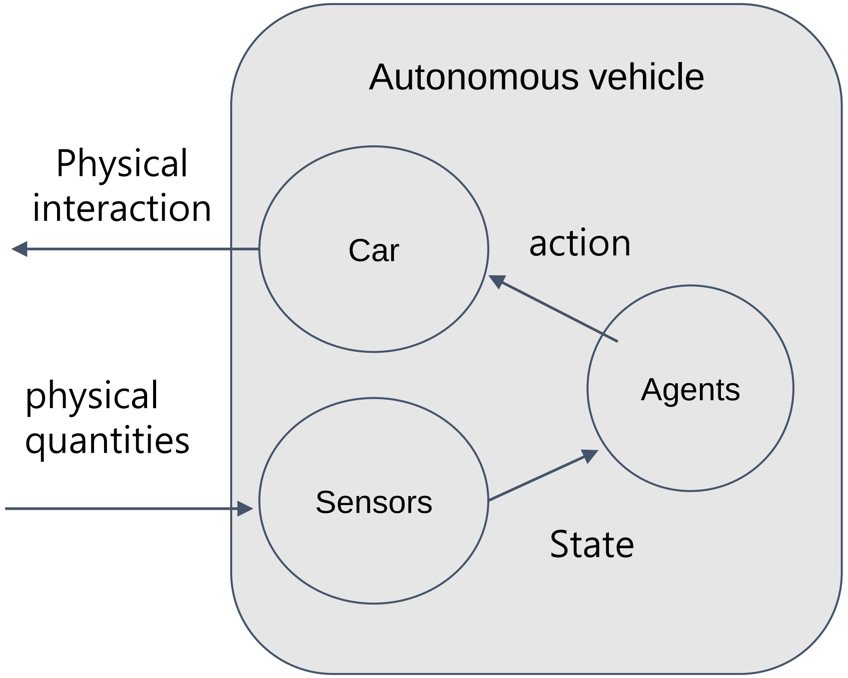
- Autonomous (자율, 自律) + driving (주행, 走行)
- Self-driving car, autonomous vehicle, driver-less car, or robotic car
- 자동차가 **자체적**으로 **주변환경**을 **인지**하고 **안전히 주행**하는 기술



Basic components for Autonomous Driving

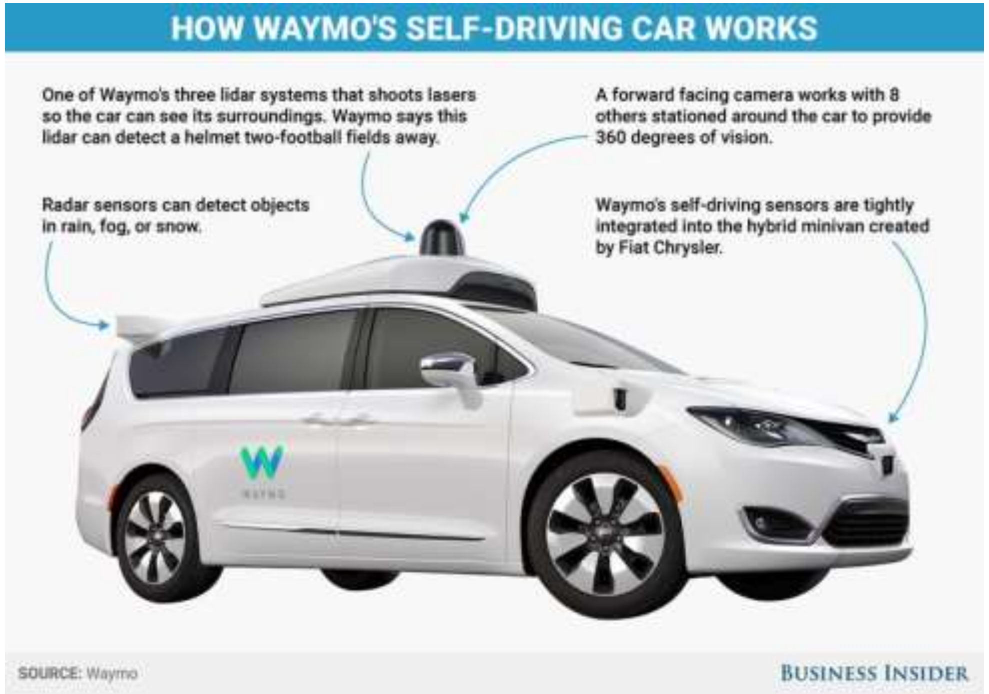
- Car: a vehicle that actually moves and the agent should control
- Sensor: a device that detect the surrounding environment.
- Agent: An object that drive the var safely for a given surrounding environment.

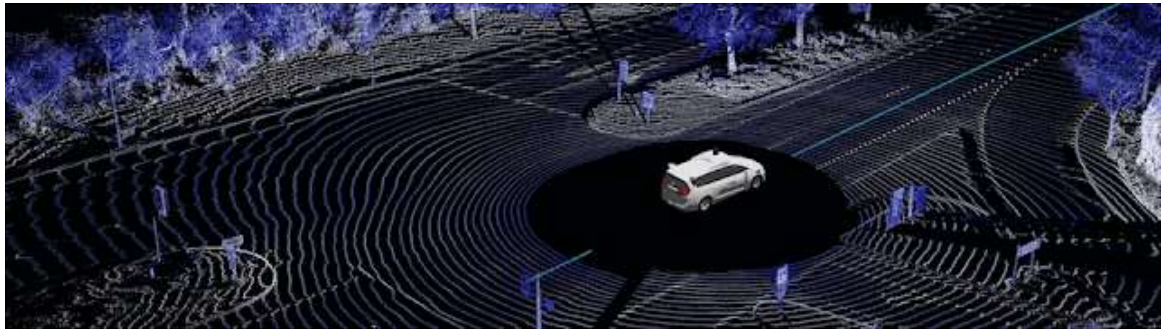
Surrounding environments



Sensors on self-driving cars

- 460 Lidar camera or rgb cameras.





360-degree Lidar map

Three-direction RGB image

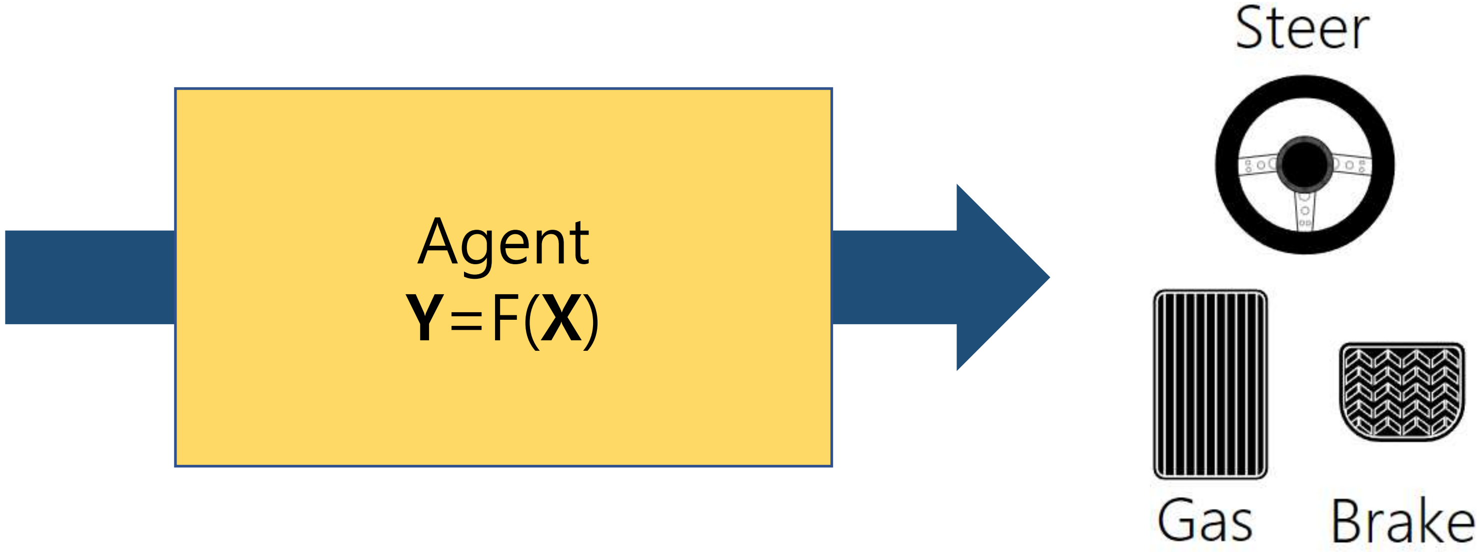
https://blog.waymo.com/2021/10/the-waymo-driver-handbook-perception.html

https://www.businessinsider.com/how-does-googles-waymo-self-driving-car-work-graphic-2017-1

Goal of Autonomous Driving

- Driving safely for a given scenario.
- 주어진 상황(state)에 따라 자동차를 안전히 조종하자.

Sensor Input **X**



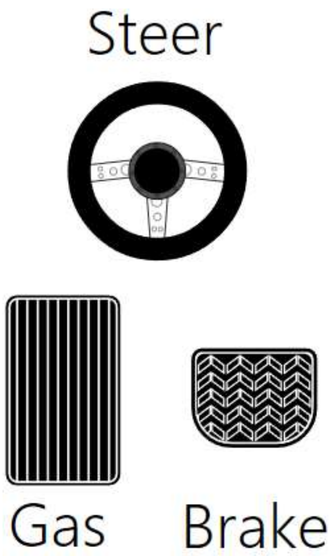
Control **Y**
(Action)

https://medium.com/apache-mxnet/analyze-driving-scenes-with-gluoncv-0-8-56ac37664977

Major Paradigms for Autonomous Driving

Sensor Input **X**

Mapping Function
Sensor input → Action
Y=F(**X**)



Control **Y**
(Action)

- Modular Pipelines
- End-to-End Learning
- Direct Perception

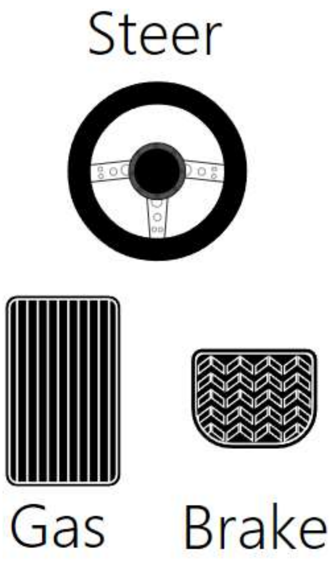
Major Paradigms for Autonomous Driving

Sensor Input **X**

Mapping Function

Sensor input → Action

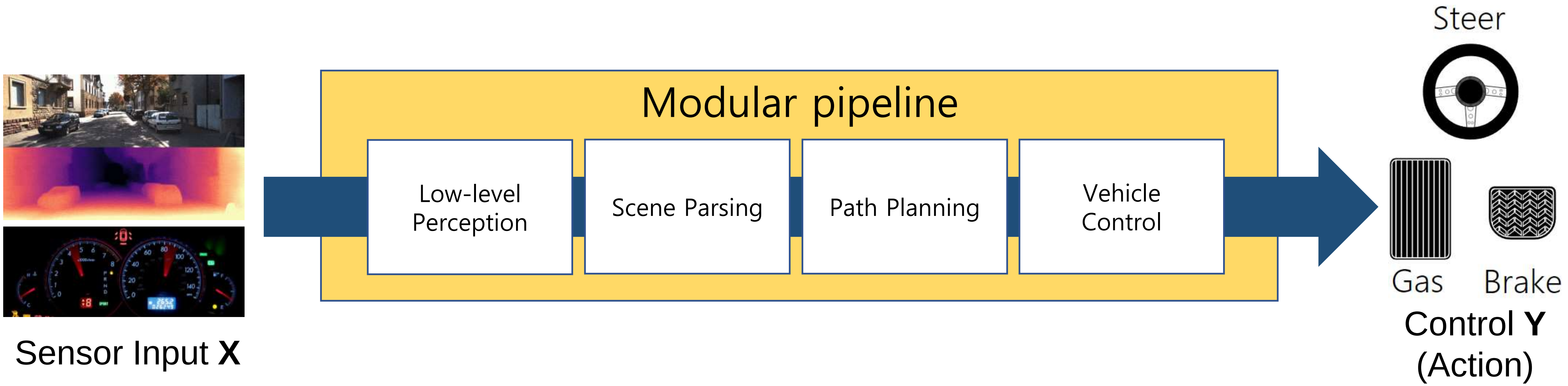
Y=F(**X**)



Control **Y**
(Action)

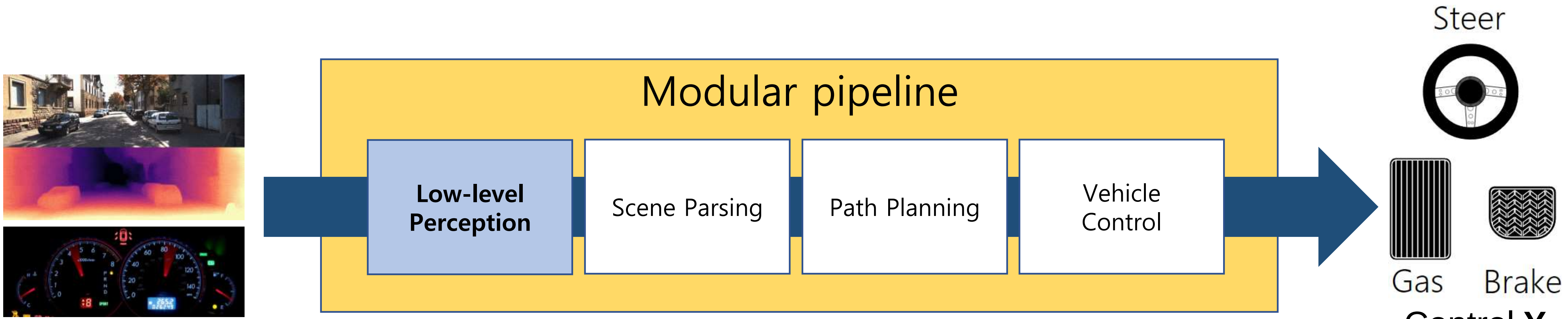
- **Modular Pipelines**
- End-to-End Learning
- Direct Perception

Modular Pipeline



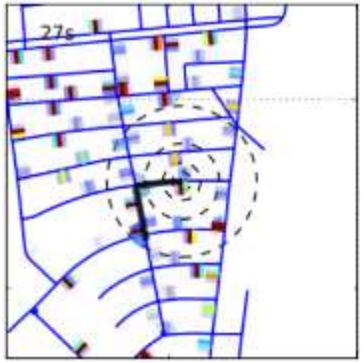
- Each module produces input of the next module.
  - Low-level Perception
  - Scene Parsing
  - Path training
  - Vehicle Control

Modular Pipeline

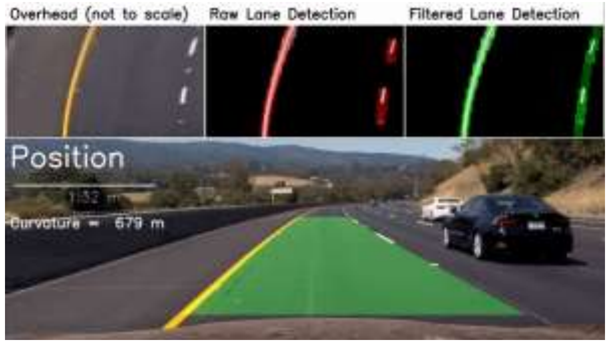


Sensor Input **X**

Control **Y**
(Action)



GPS Location



Lane detection

Detecting moving cars

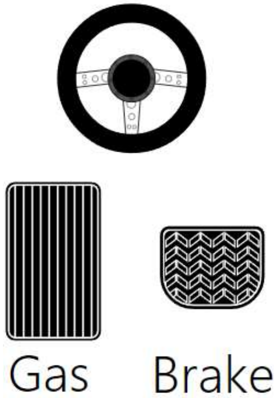
Modular Pipeline

Sensor Input **X**

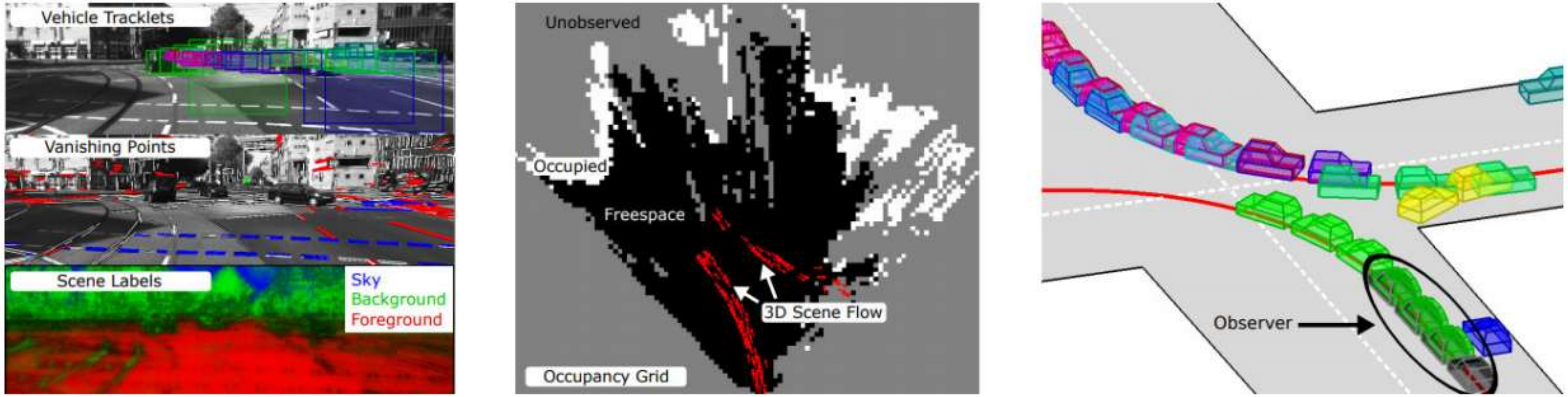
Modular pipeline

Low-level Perception → **Scene Parsing** → Path Planning → Vehicle Control

Steer



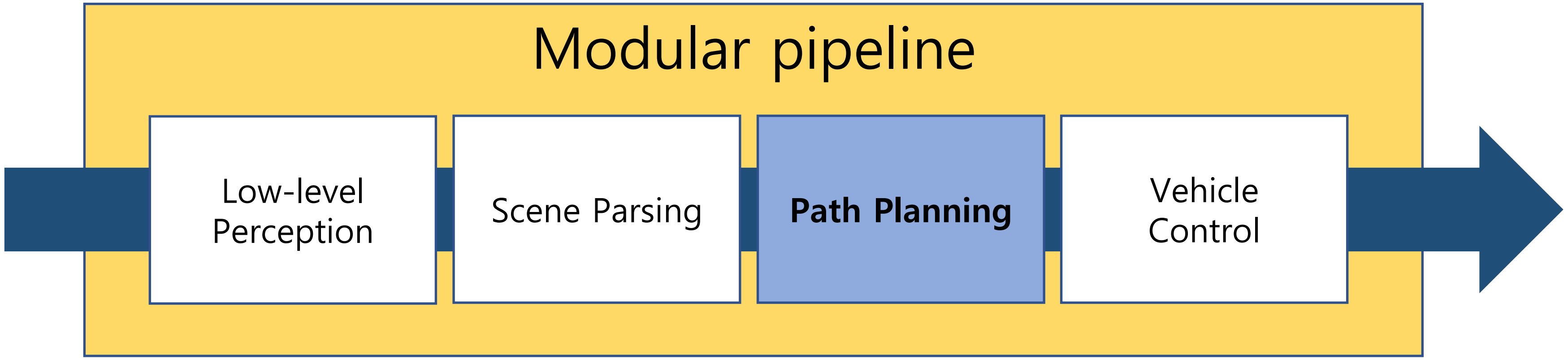
Control **Y**
(Action)



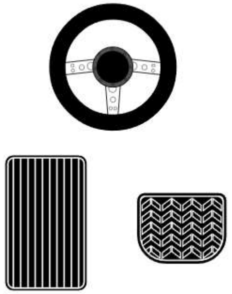
Parsing detected objects into one world space

Modular Pipeline

Sensor Input **X**



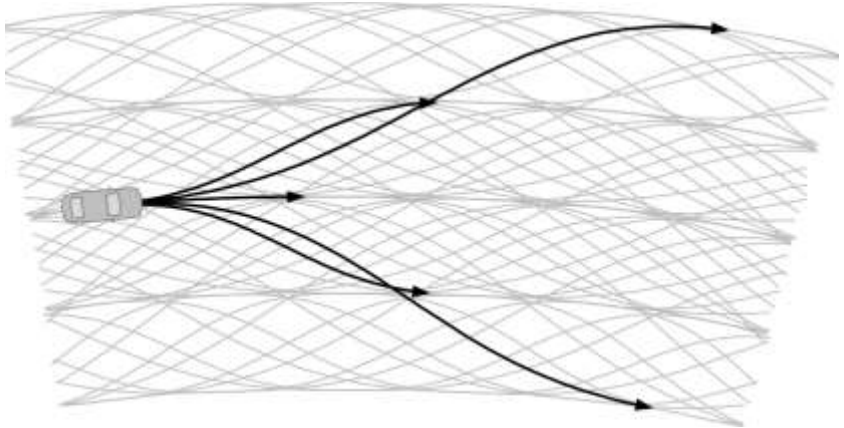
Steer



Gas Brake

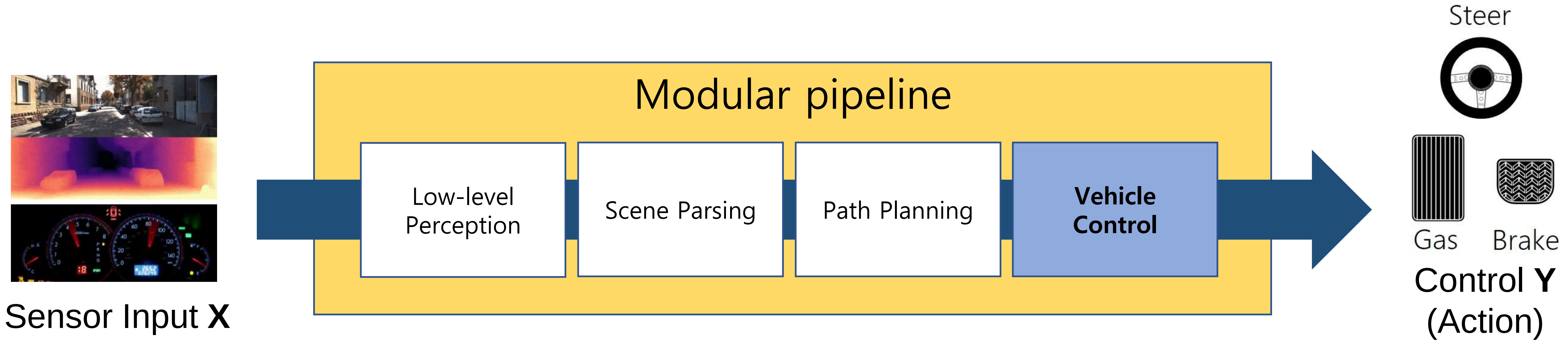
Control **Y**
(Action)

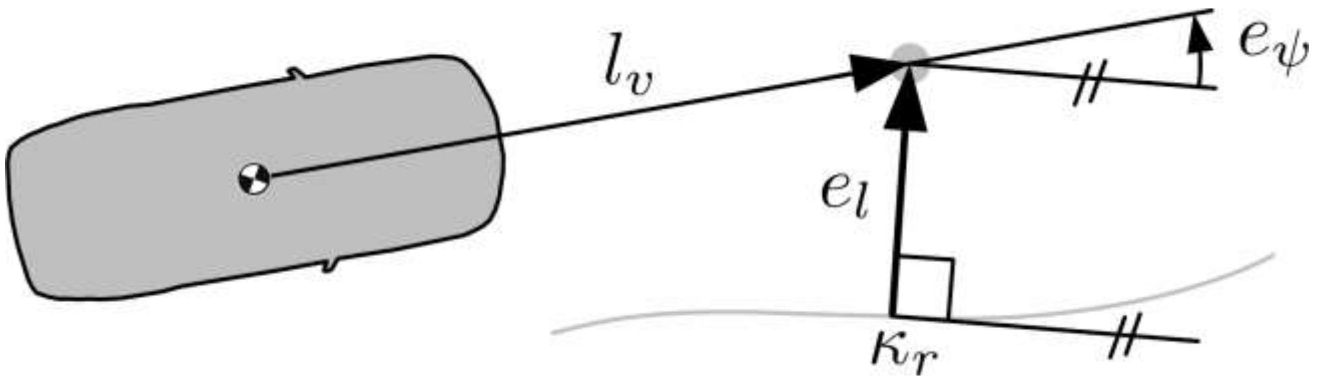
Which path is the fastest one?



How to move a car on the road?

Modular Pipeline





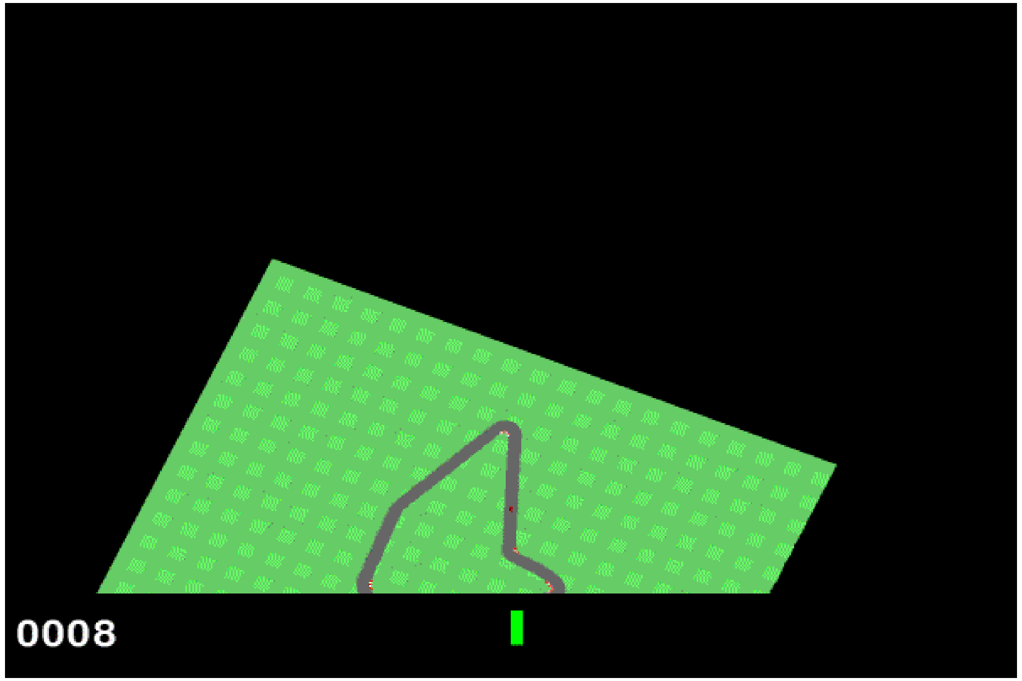
In order to follow the selected path,
How much should we steer the handle?
What speed should we go in?

Our Car Environment

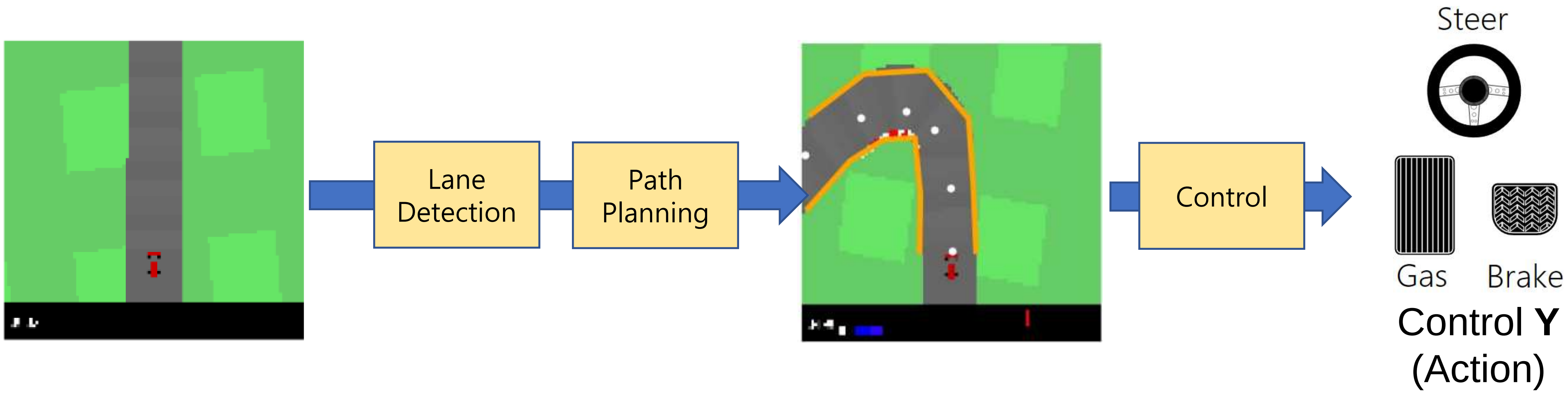
- Goal: implement a modular pipeline framework.

- Simulator: **OpenAI GYM**
  - https://www.gymlibrary.ml/
  - We will use Box2D-CarRacing

- CarRacing information
  - Action: steering, acceleration, brake
  - Sensor input: 96x96x3 screen
    - It shows car's states and path information.



Modular pipeline overview



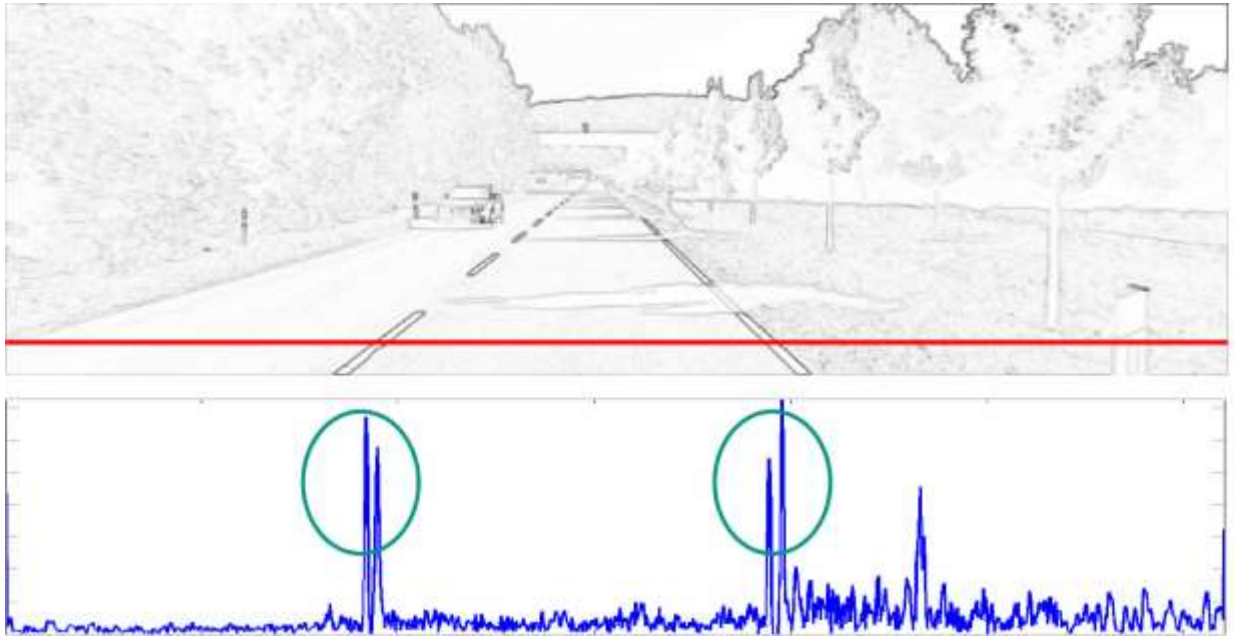
- Implement simplified version of modular pipeline.
- You will understand basic concepts and get experiences of developing a simple self-driving application.

Lane marking & Lane detection

Lane mark detection

- Using a gradient map or an edge-filtered image, we can detect lane marks by thresholding.
- Consider points for which opposite gradient exists in vicinity.

An road image and its gradient map



An1D profile for lane marking detection

Edge Detection

- By convolving an image with edge filters, two directional gradient maps are obtained.
- Other edge kernels can be used ([1 0 -1]).

-1	0	+1
-2	0	+2
-1	0	+1

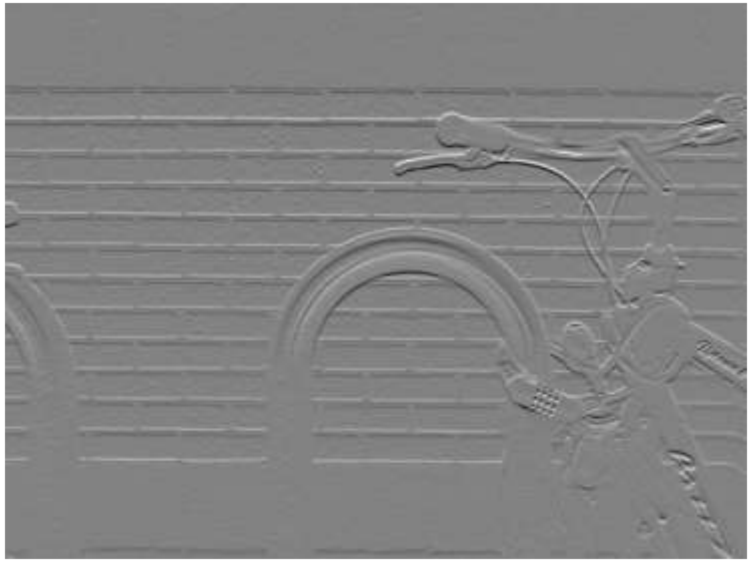
Gx

+1	+2	+1
0	0	0
-1	-2	-1

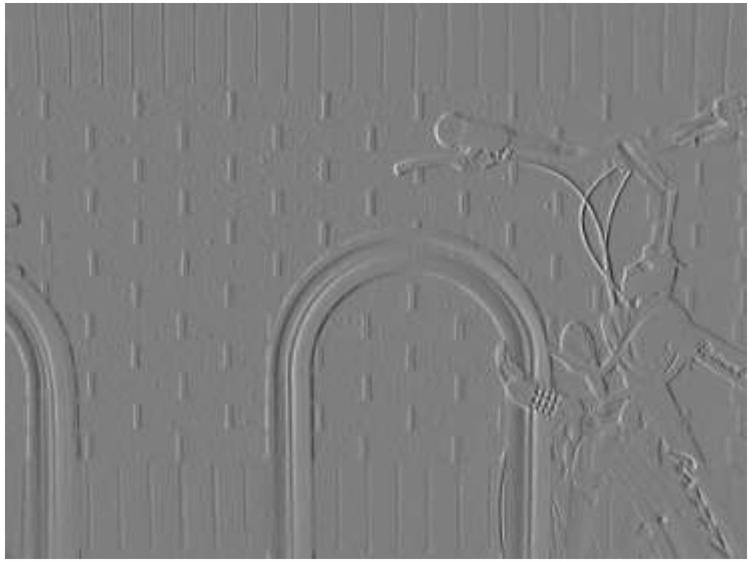
Gy

Sobel edge kernels

RGB Image



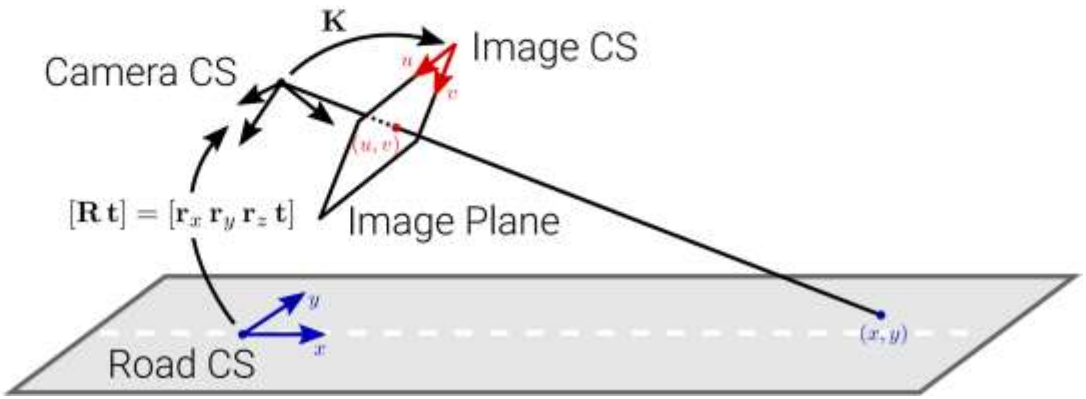
Gradient y



Gradient x

Inverse Perspective Mapping

- In common, roads are on the plane.
- If the 3D transform is known, we can project the road image on the ground plane.



The 3D overview of inverse perspective mapping

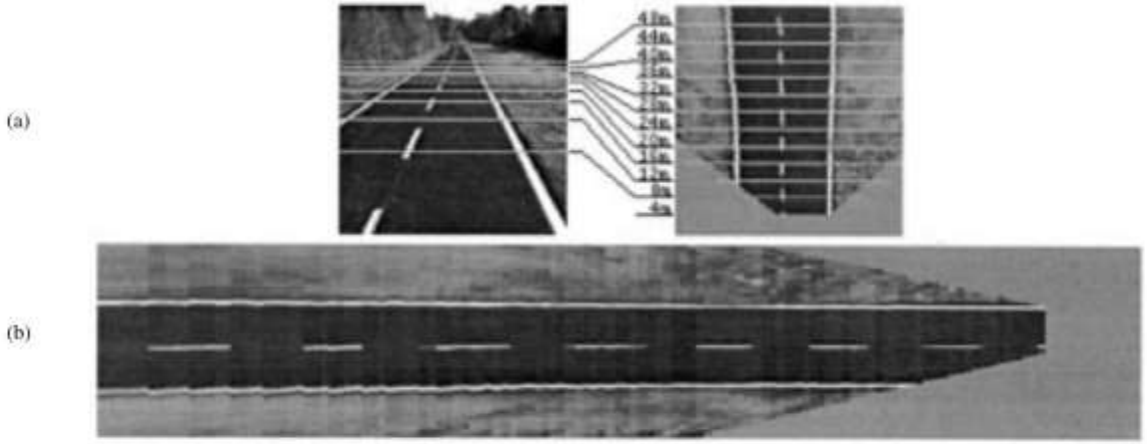
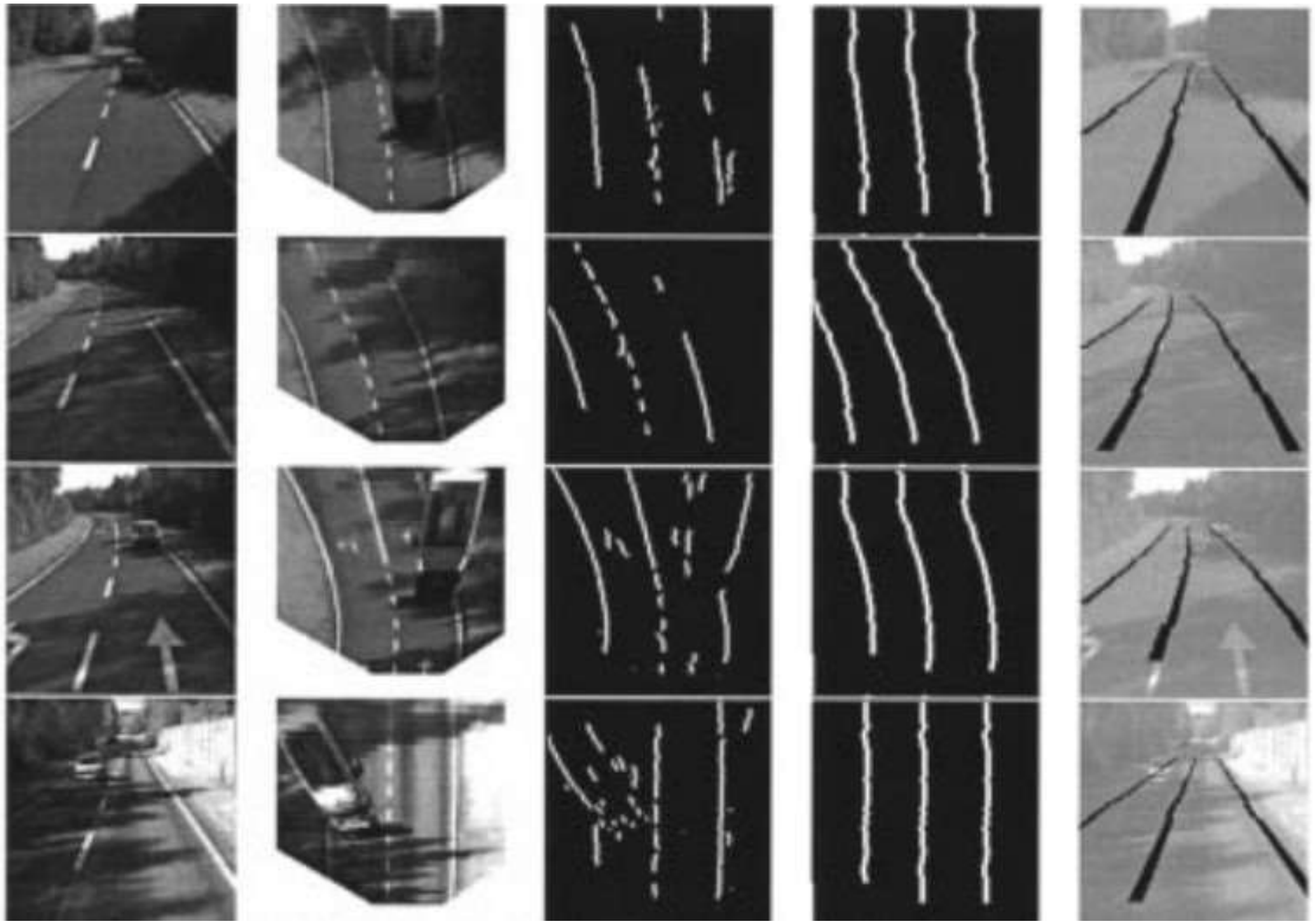


Fig. 8. (a) Horizontal calibration of the MOB-LAB vision system. (b) Rotated version of the remapped image considering an aspect ratio of 1 : 1.

Inverse Perspective Mapping.

Inverse Perspective Mapping



Projected road maps and detected lanes

Parametric Lane Marking Estimation

- In order to navigate the car, we need to fit detected mark pixels to a more semantically meaningful curve model.

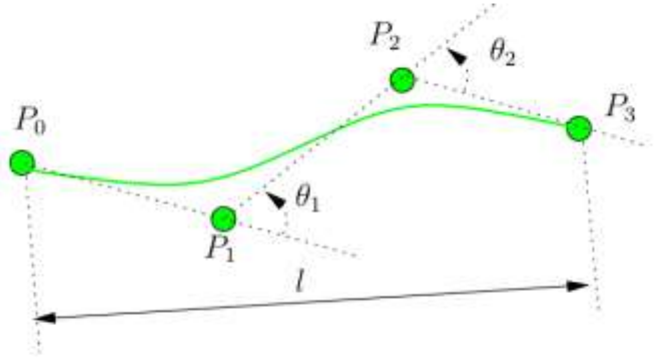


Fig. 7. Spline score computation.

Algorithm 1 RANSAC Spline Fitting

for $i = 1$ to $numIterations$ **do**
  $points$=getRandomSample()
  $spline$=fitSpline($points$)
  $score$=computeSplineScore($spline$)
  if $score > bestScore$ **then**
    $bestSpline = spline$
  end if
end for

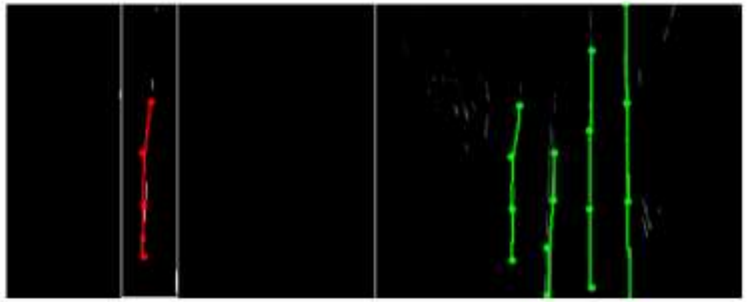


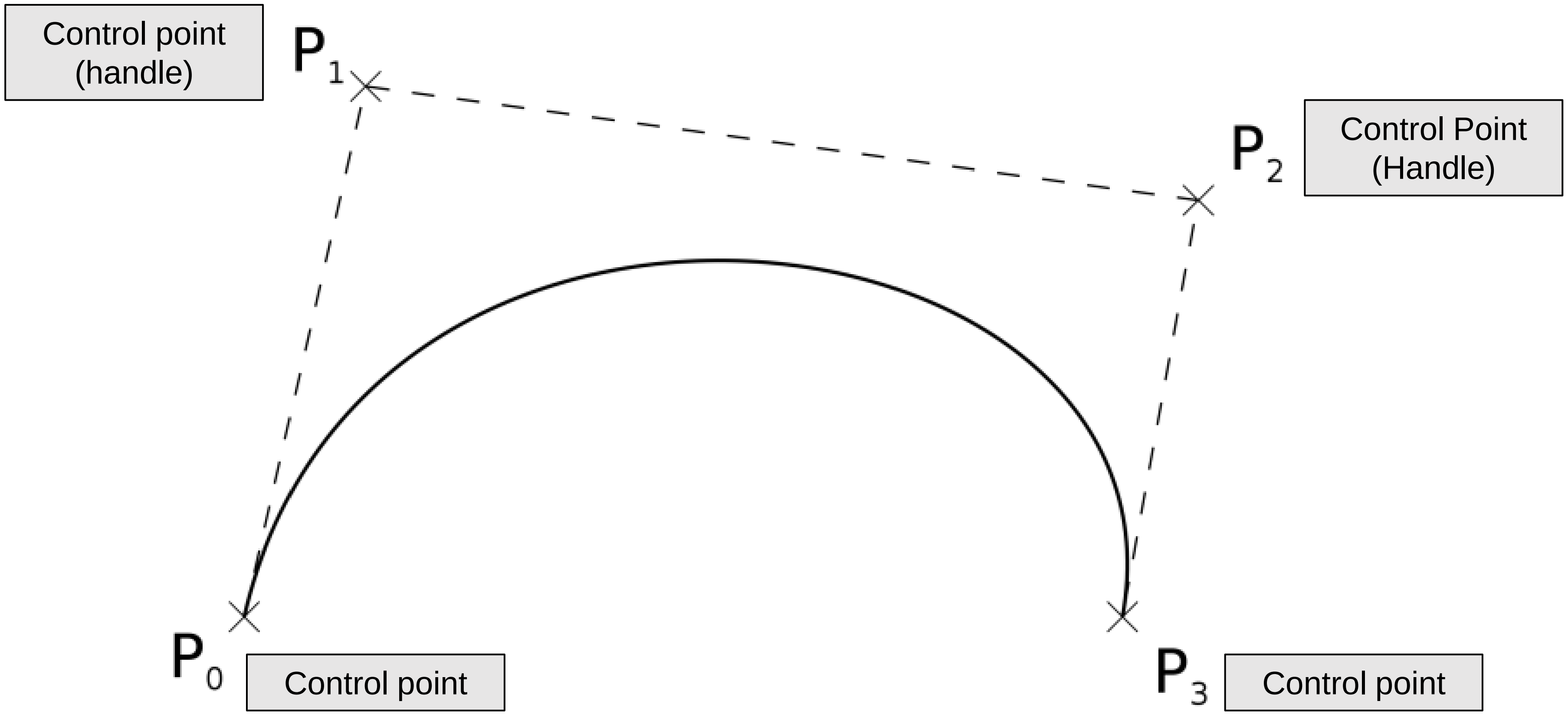
Fig. 8. RANSAC Spline fitting. Left: one of four windows of interest (white) obtained from previous step with detected spline (red). Right: the resulting splines (green) from this step

Fig. 10. Post-processing splines. Left: splines before post-processing in blue. Right: splines after post-processing in green. They appear longer and localized on the lanes.

Curve

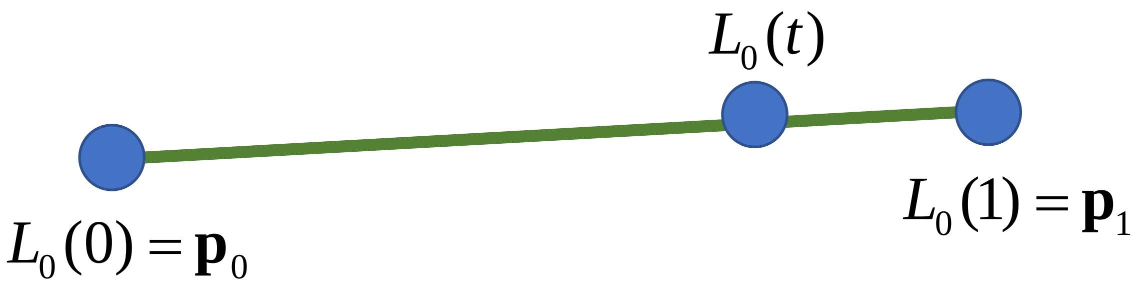
Bezier Curve

- A polynomial curve defined by control points.



Linear Bezier Curve

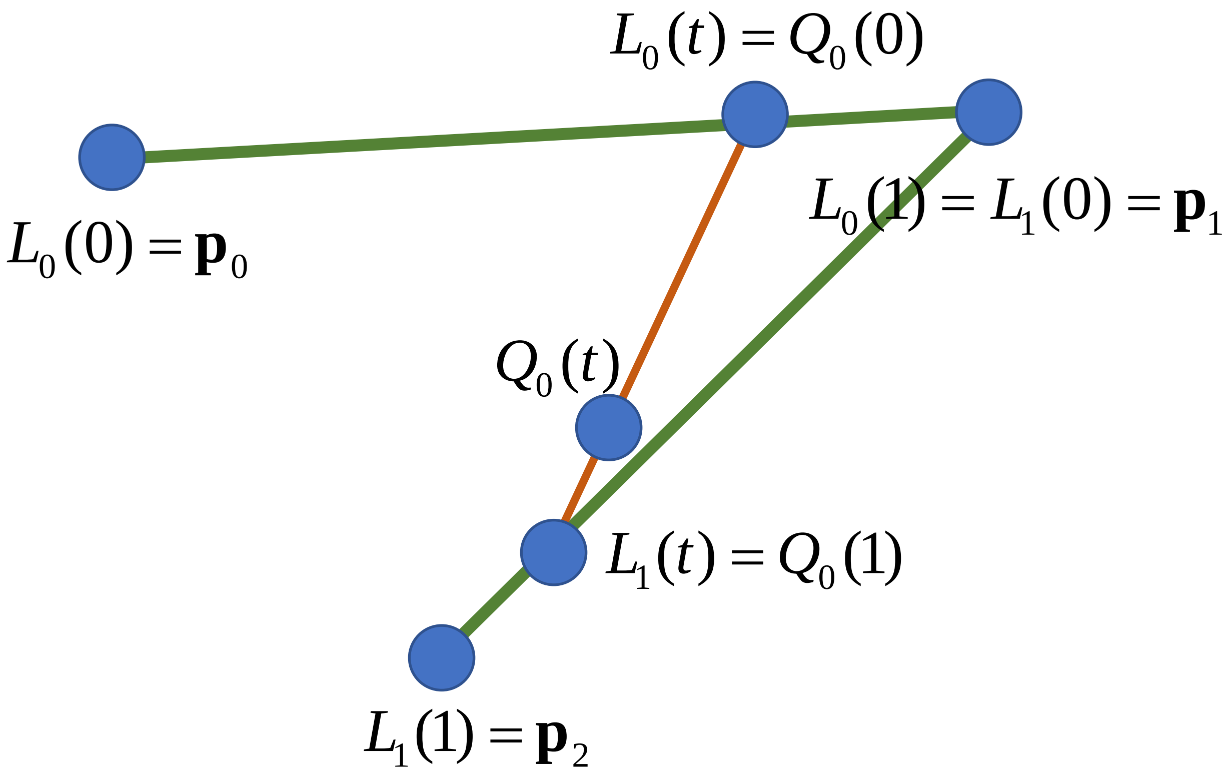
- Analogous to linear interpolation



$$L_0(t) = (1-t)\mathbf{p}_0 + t\mathbf{p}_1$$

Quadratic Bezier Curve

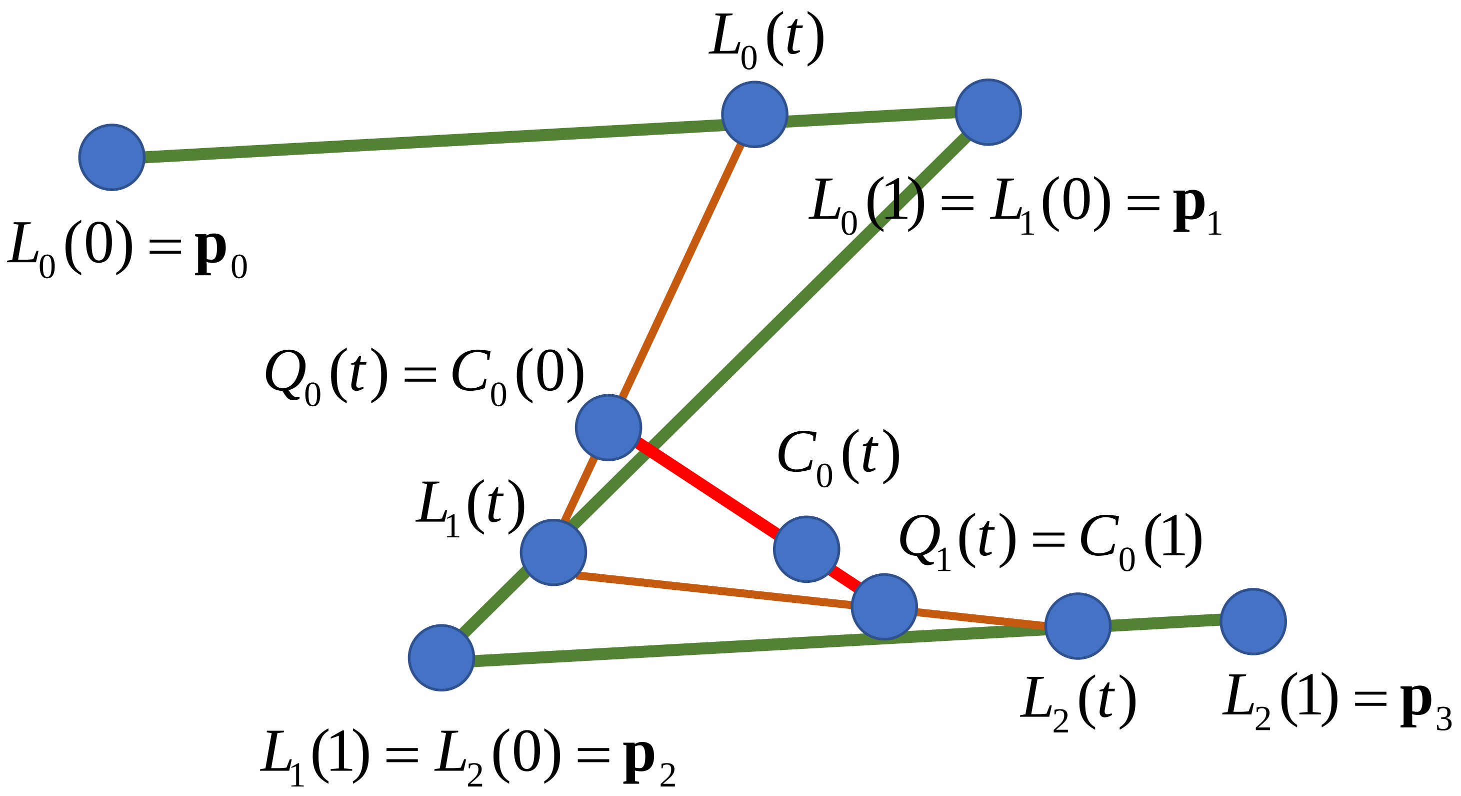
- Interpolation of two linearly interpolated points.



$$L_0(t) = (1-t)\mathbf{p}_0 + t\mathbf{p}_1$$
$$L_1(t) = (1-t)\mathbf{p}_1 + t\mathbf{p}_2$$
$$Q_0(t) = (1-t)L_0(t) + tL_1(t)$$
$$Q_0(t) = (1-t)^2\mathbf{p}_0 + 2(1-t)t\mathbf{p}_1 + t^2\mathbf{p}_2$$

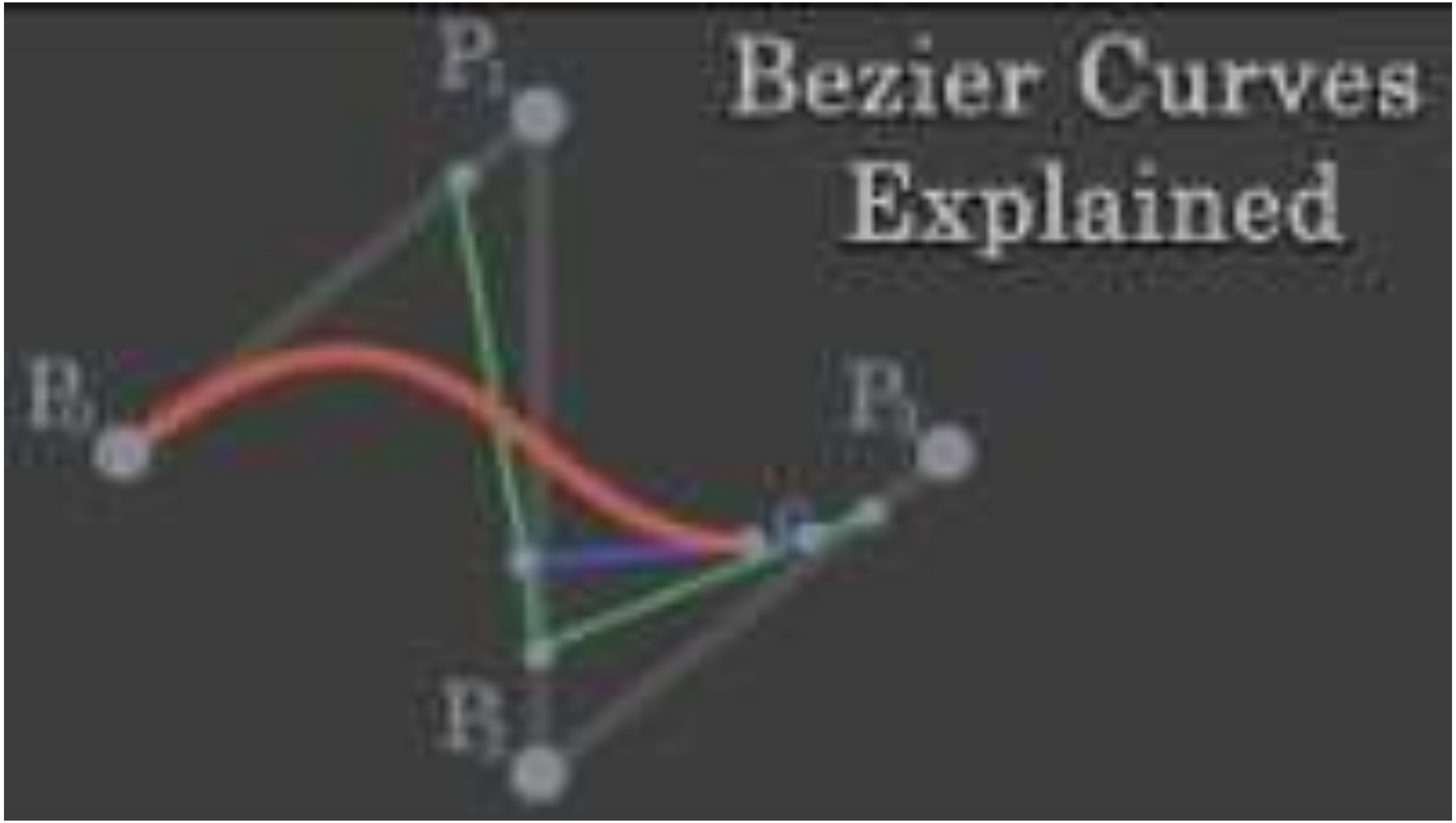
Cubic Bezier Curve

- Interpolation of quadratic points.



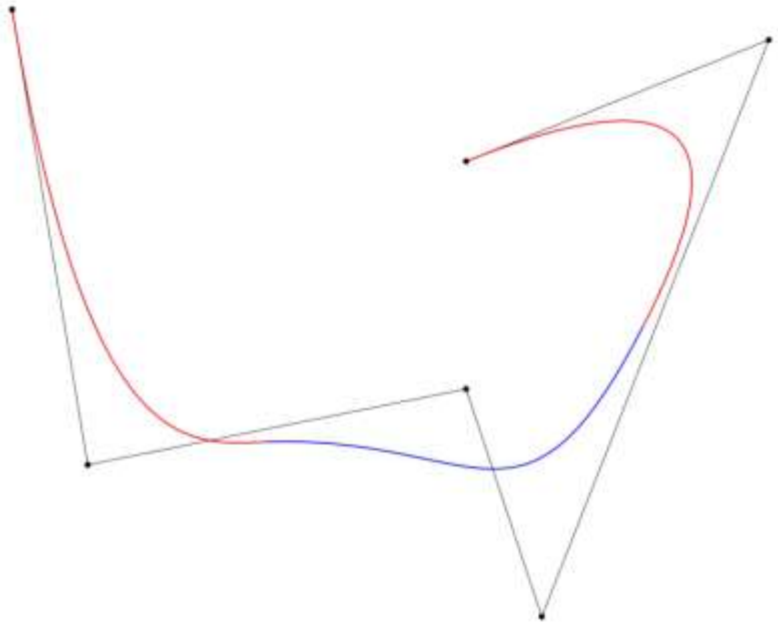
$$L_0(t) = (1-t)\mathbf{p}_0 + t\mathbf{p}_1$$
$$L_1(t) = (1-t)\mathbf{p}_1 + t\mathbf{p}_2$$
$$L_2(t) = (1-t)\mathbf{p}_2 + t\mathbf{p}_3$$
$$Q_0(t) = (1-t)L_0(t) + tL_1(t)$$
$$Q_1(t) = (1-t)L_1(t) + tL_2(t)$$
$$C_0(t) = (1-t)Q_0(t) + tQ_1(t)$$

Bezier Curve animation

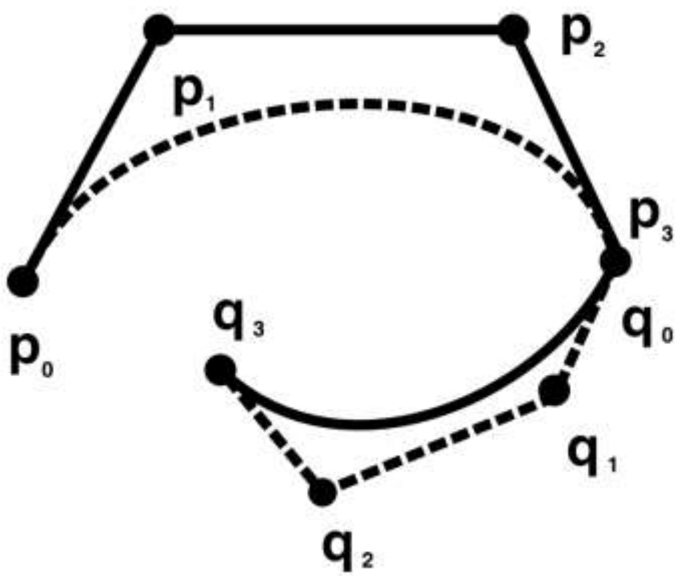


B(Basis)-Spline Curve

- Curve defined by a list of control points and the degree.
- A piece-wise polynomial curve (not same as a piece-wise Bezier curve).



B-spline curve

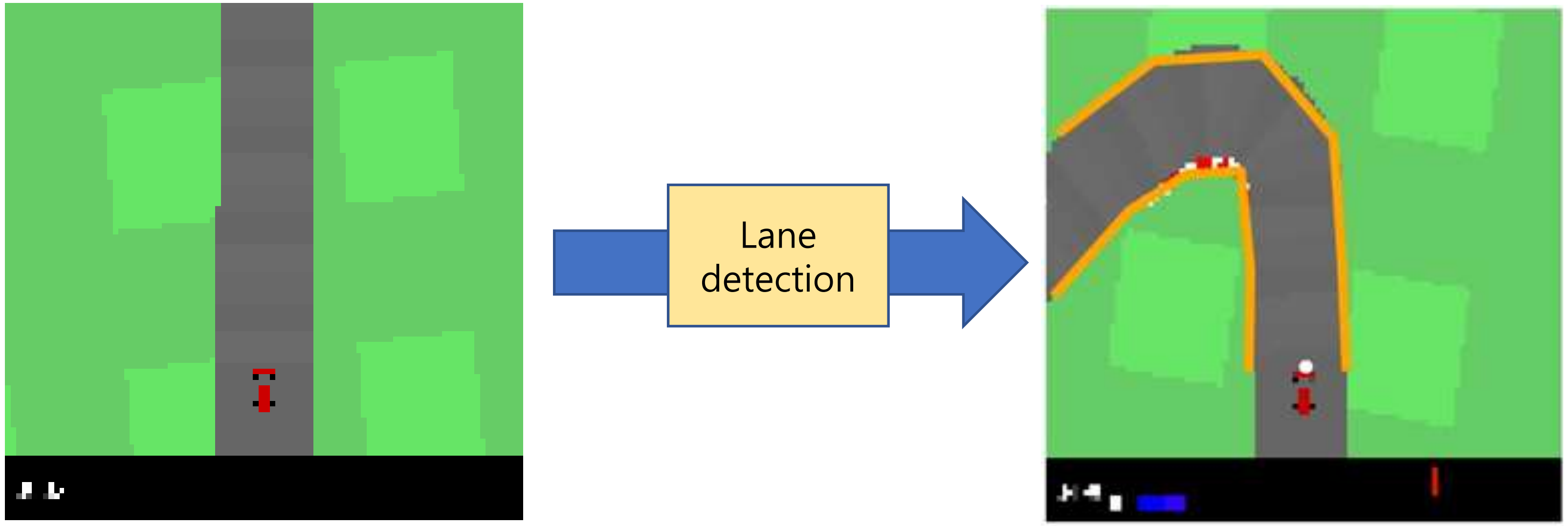


Piece-wise Bezier curve

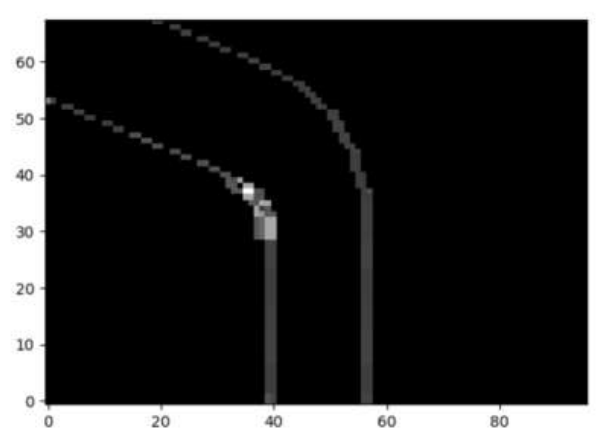
Experiment

Lane Detection

- Three steps
  - Edge detection: gradient thresholding
  - Assign edges to lane boundaries: successive nearest edge search
  - Spline fitting: parametric spline curve fitting



Lane Detection



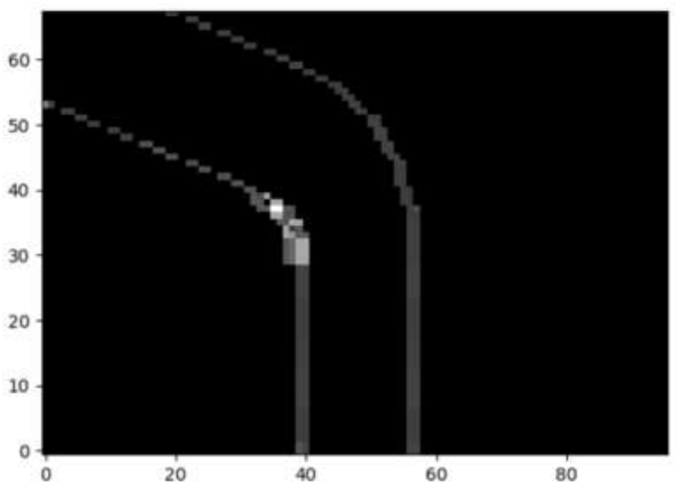
An gradient image with clipping

- Template
  - *lane detection.py*
  - *test lane detection.py* for testing
- **Edge detection:**
  - Translate the state image to a grey scale image and crop out the part above the car
    - *LaneDetection.cut_gray()*
  - Derive the absolute value of the gradients of the grey scale image and apply thresholding to ignore unimportant gradients.
    - *LaneDetection.edge_detection()*
  - Determine arguments of local maxima of absolute gradient per pixel row
    - *LaneDetection.find_maxima_gradient_rowwise()*

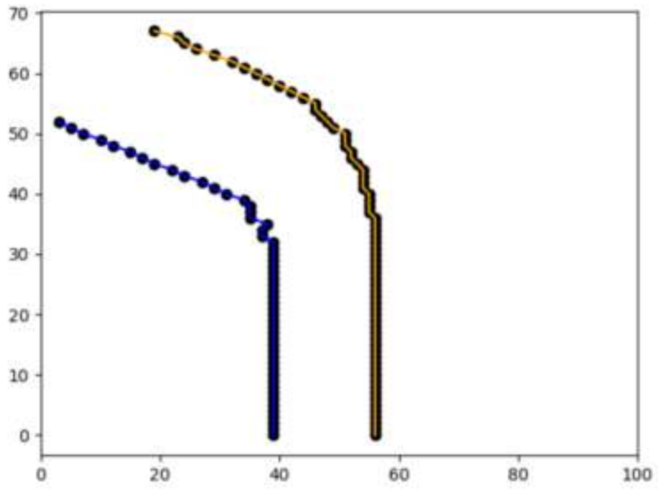
    Hint: use for example scipy.signal.find_peaks()
    https://docs.scipy.org/doc/scipy/reference/generated/scipy.signal.find_peaks.html

Lane Detection

- **Assign Edges to Lane Boundaries**:
  - Find arguments of local maxima in the image row closest to the car
    - ➢ LaneDetection.find_first_lane_point() (already implemented)
  - Assign the edges to the lane boundaries by successively searching for the nearest neighboring edge/maximum along each boundary
    - ➢ LaneDetection.lane_detection()



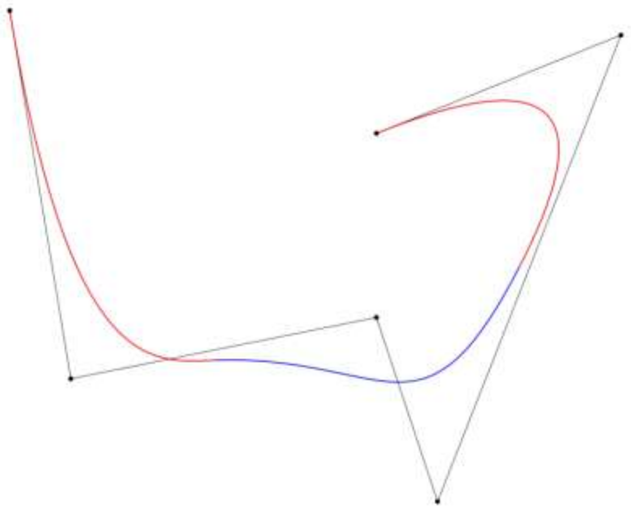
An gradient image with clipping



Peak points

Lane Detection

- **Spline Fitting**:
  - Fit a parametric spline to each lane boundary
    - ➢ LaneDetection.lane detection()
  - Use *scipy.interpolate.splprep* for fitting and *scipy.interpolate.splev* for evaluation (https://docs.scipy.org/doc/scipy/reference/generated/scipy.interpolate.splprep.html#id3)



Given a list of points, which represents a curve in 2-dimensional space parametrized by s, find a smooth approximating spline curve g(s).

Correct Lane detection

Spline Fitting

- *scipy.interpolate.splprep* will return parameters but we will take only the first one.

```
lane_boundary,_ = splprep([lane_boundary_points[1:,0], lane_boundary_points[1:,1]], s=self.spline_smoothness, k=2)
```

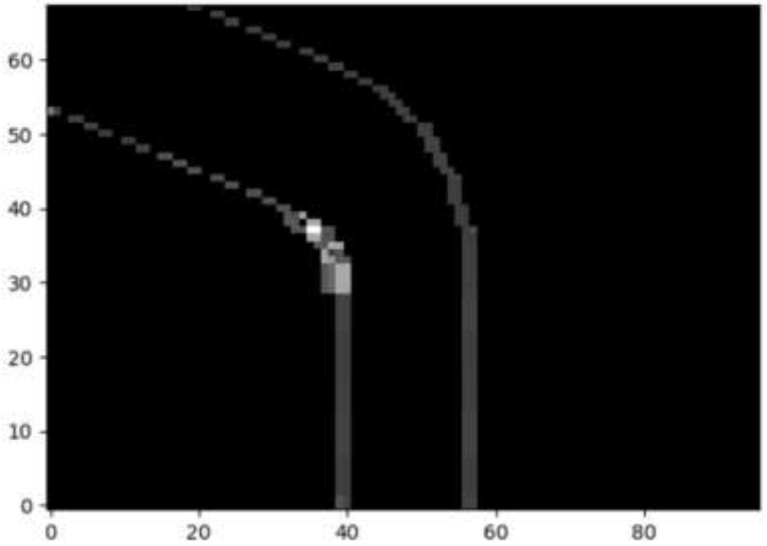
- With those parameters and function *scipy.interpolate.splev*, we can extract points on the curve.

```
t = np.linspace(0, 1, 5) # t = [0, 0.25, 0.5, 0.75, 1]
Interpolated_lane_boundary_points = np.array(splev(t, self.lane_boundary))
```

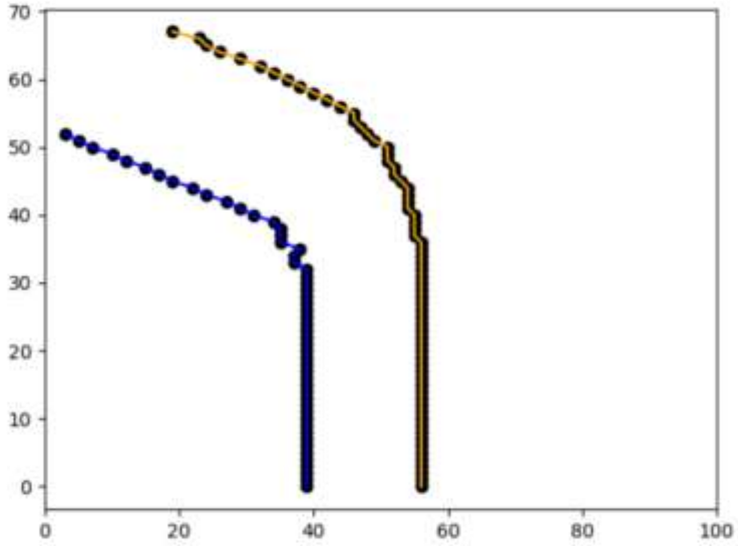
Lane Detection

- **Testing:**
  - Find a good crop for the part above the car, a good approach to assign edges to lane boundaries and a good choice of parameters for the gradient threshold and the spline smoothness.
  - Try to find failure cases

Lane Detection



An gradient image with clipping



Peak points

Correct Lane detection