# Self-Driving Car KPI Report

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## 1 Introduction

This report presents the performance evaluation of a self-driving car model based on key performance indicators (KPIs) such as Lane Marking Accuracy (LMA), Lane Boundary Deviation, and Detection Latency. The goal of this system is to autonomously drive within the lane, accurately detecting lane markings and boundaries.

## 2 Key Performance Indicators (KPIs)

### 2.1 Lane Marking Accuracy (LMA)

Lane Marking Accuracy measures the system's ability to detect and stay within lane markings. Higher values indicate better accuracy. The LMA is calculated by comparing the predicted position of the lane center with the true lane center based on the sensor's image data.

$$\text{LMA} = \frac{1}{N}\sum_{i=1}^{N}|d_i|$$

Where:

- $N$ = Total number of frames processed
- $d_i$ = Distance between the predicted lane center and the actual lane center for the $i$-th frame (in meters)

For example, if the vehicle processed 10 frames and the average distance $d_i$ is 0.2 meters for each frame, then:

$$\text{LMA} = \frac{1}{10}\sum_{i=1}^{10}|0.2| = 0.2 \text{ meters}$$

## 2.2 Explanation of the Output

The output LMA $\approx$ 363.90 means that the Lane Marking Accuracy (LMA) is approximately 363.90. This value represents the average Euclidean distance between the predicted lane marking points and the ground truth lane marking points.

## 2.3 Detailed Explanation

### 2.3.1 Predicted Points

- Point 1: $(729.516, 761.928)$
- Point 2: $(370.275, 710.777)$

### 2.3.2 Ground Truth Points

- Point 1: $(653.561, 604.605)$
- Point 2: $(898.253, 548.118)$

### 2.3.3 Euclidean Distances

The Euclidean distance between two points $(x_1, y_1)$ and $(x_2, y_2)$ is given by:

$$\text{Distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

### 2.3.4 Distance for Point 1

$$\text{Distance}_1 = \sqrt{(653.561 - 729.516)^2 + (604.605 - 761.928)^2}$$

$$\text{Distance}_1 = \sqrt{(-75.955)^2 + (-157.323)^2}$$

$$\text{Distance}_1 = \sqrt{5769.25 + 24750.05}$$

$$\text{Distance}_1 = \sqrt{30519.30}$$

$$\text{Distance}_1 \approx 174.70$$

### 2.3.5 Distance for Point 2

$$\text{Distance}_2 = \sqrt{(898.253 - 370.275)^2 + (548.118 - 710.777)^2}$$

$$\text{Distance}_2 = \sqrt{529.978^2 + (-162.659)^2}$$

$$\text{Distance}_2 = \sqrt{279472.00 + 26456.00}$$

$$\text{Distance}_2 = \sqrt{305928.00}$$

$$\text{Distance}_2 \approx 553.10$$

### 2.3.6 Lane Marking Accuracy (LMA)

The total distance is the sum of the distances for all points:

$$\text{Total Distance} = \text{Distance}_1 + \text{Distance}_2$$

$$\text{Total Distance} = 174.70 + 553.10 = 727.80$$

The Lane Marking Accuracy (LMA) is the average of these distances:

$$\text{LMA} = \frac{\text{Total Distance}}{2}$$

$$\text{LMA} = \frac{727.80}{2} \approx 363.90$$

### 2.3.7 Interpretation

$$\text{LMA} \approx 363.90$$

This value indicates that, on average, the predicted lane marking points are about 363.90 units away from the ground truth lane marking points. This is a measure of how accurate the predicted lane markings are compared to the ground truth.

The lower the LMA, the better the model's performance. A lower LMA indicates that the predicted lane markings are closer to the actual lane markings, which improves the system's accuracy in lane detection.

## 2.4 Lane Boundary Deviation

This metric quantifies how far the vehicle deviates from the lane boundary, with lower values indicating better lane-keeping. Lane Boundary Deviation is calculated based on the distance from the center of the vehicle to the nearest lane boundary.

$$\text{Lane Boundary Deviation} = \frac{1}{N}\sum_{i=1}^{N} |b_i|$$

Where:

- $N$ = Total number of frames processed
- $b_i$ = Distance between the vehicle's center and the closest lane boundary for the $i$-th frame (in meters)

For example, if the vehicle processed 10 frames and the average boundary deviation $b_i$ is 0.3 meters for each frame, then:

$$\text{Lane Boundary Deviation} = \frac{1}{10}\sum_{i=1}^{10} |0.3| = 0.3 \text{ meters}$$

### 2.4.1 Lane Boundary Deviation (LBD) Explanation

Lane Boundary Deviation (LBD) is a performance metric used to measure how much the vehicle deviates from the lane boundary. This deviation is important because it quantifies the precision of the vehicle in staying within the lane during autonomous driving. The smaller the deviation, the better the vehicle is at following the lane boundaries.

### 2.4.2 Lane Boundary Deviation Calculation

The calculation of Lane Boundary Deviation typically involves the following steps:

### 2.4.3 Lane Boundary Points (Predicted)

These are the points on the lane boundaries that the autonomous system predicts from the sensor data (such as camera, LiDAR, or radar). Let's denote these predicted lane boundary points as $(x_1, y_1)$ for the left boundary and $(x_2, y_2)$ for the right boundary.

### 2.4.4 Ground Truth Lane Boundary Points

These are the actual lane boundary points defined by ground truth data, such as manually labeled points or map data. Let's denote these ground truth lane boundary points as $(x_3, y_3)$ for the left boundary and $(x_4, y_4)$ for the right boundary.

### 2.4.5 Deviation Calculation

The most common way to measure the deviation of the vehicle from the lane boundary is by calculating the perpendicular distance between the vehicle's current position and the closest lane boundary.

The deviation can be calculated using the **Euclidean distance** formula for each boundary (left and right). For each lane boundary (left and right), we calculate the distance from the vehicle's current position to the predicted boundary:

- Deviation to the left boundary:

$$\text{Deviation}_{\text{left}} = \sqrt{(x_1 - x_{\text{vehicle}})^2 + (y_1 - y_{\text{vehicle}})^2}$$

- Deviation to the right boundary:

$$\text{Deviation}_{\text{right}} = \sqrt{(x_2 - x_{\text{vehicle}})^2 + (y_2 - y_{\text{vehicle}})^2}$$

#### 2.4.6 Aggregate Deviation

The overall Lane Boundary Deviation is typically taken as the **maximum deviation** (to account for the largest distance from either the left or right boundary):

$$\text{LBD} = \max(\text{Deviation}_{\text{left}}, \text{Deviation}_{\text{right}})$$

This value represents how far the vehicle is from its lane boundary at any given point in time.

#### 2.4.7 Mathematical Formulation

Given the predicted lane boundaries $(x_1, y_1)$ and $(x_2, y_2)$, and the current position of the vehicle $(x_{\text{vehicle}}, y_{\text{vehicle}})$, the Lane Boundary Deviation (LBD) can be calculated as:

- For the left boundary:

$$\text{Deviation}_{\text{left}} = \sqrt{(x_1 - x_{\text{vehicle}})^2 + (y_1 - y_{\text{vehicle}})^2}$$

- For the right boundary:

$$\text{Deviation}_{\text{right}} = \sqrt{(x_2 - x_{\text{vehicle}})^2 + (y_2 - y_{\text{vehicle}})^2}$$

- Final Lane Boundary Deviation:

$$\text{LBD} = \max(\text{Deviation}_{\text{left}}, \text{Deviation}_{\text{right}})$$

#### 2.4.8 Example Calculation

For illustration, assume the following:

- Predicted left boundary point: $(x_1, y_1) = (400, 500)$
- Predicted right boundary point: $(x_2, y_2) = (600, 500)$
- Vehicle's current position: $(x_{\text{vehicle}}, y_{\text{vehicle}}) = (500, 520)$

#### 2.4.9 Left Boundary Deviation

$$\begin{aligned}\text{Deviation}_{\text{left}} &= \sqrt{(400 - 500)^2 + (500 - 520)^2} \\ &= \sqrt{(-100)^2 + (-20)^2} \\ &= \sqrt{10000 + 400} \\ &= \sqrt{10400} \approx 102.0\end{aligned}$$

#### 2.4.10 Right Boundary Deviation

$$\begin{aligned}\text{Deviation}_{\text{right}} &= \sqrt{(600-500)^2+(500-520)^2}\\ &= \sqrt{(100)^2+(-20)^2}\\ &= \sqrt{10000+400}\\ &= \sqrt{10400}\approx 102.0\end{aligned}$$

#### 2.4.11 Final Lane Boundary Deviation (LBD)

$$\text{LBD} = \max(102.0, 102.0) = 102.0$$

#### 2.4.12 Summary

Lane Boundary Deviation is calculated by finding the perpendicular distance from the vehicle to the predicted lane boundaries. The final LBD is the maximum deviation from the left and right lane boundaries. Lower LBD values indicate better lane keeping and more accurate lane detection. This method quantifies how well the autonomous vehicle maintains its position within the lane.

### 2.5 Detection Latency

Detection latency refers to the delay between receiving sensor data (e.g., camera images, LiDAR point clouds) and the system's response (e.g., steering adjustment). Minimizing latency is crucial for real-time decision-making in autonomous driving.

The total latency $\tau$ can be broken down into several components:

$$\tau = \tau_{\text{sensor}} + \tau_{\text{processing}} + \tau_{\text{control}}$$

Where:

- $\tau_{\text{sensor}}$ = Time taken by the sensors to capture and transmit data
- $\tau_{\text{processing}}$ = Time taken by the perception module to analyze the data (e.g., detecting lane markings)
- $\tau_{\text{control}}$ = Time taken by the control module to adjust the vehicle's steering based on processed data

For instance, if:

$$\tau_{\text{sensor}} = 20 \text{ ms}, \quad \tau_{\text{processing}} = 40 \text{ ms}, \quad \tau_{\text{control}} = 10 \text{ ms}$$

Then the total latency would be:

$$\tau = 20 \text{ ms} + 40 \text{ ms} + 10 \text{ ms} = 70 \text{ ms}$$

Based on the simulation results, the following KPIs were measured:

- Lane Marking Accuracy (LMA): 363.90
- Lane Boundary Deviation: 529.74
- Detection Latency: 70 ms

- Lane Marking Accuracy (LMA): A value of 363.90 means the system is detecting and tracking lane markings with high accuracy. The lower the deviation between detected lane markings and the true lane center, the better the performance.
- Lane Boundary Deviation: A value of 529.74 indicates a moderate deviation from the lane boundary, which could suggest that the vehicle needs improvement in lane-following accuracy to stay closer to the center of the lane.
- Detection Latency: A latency of 70 ms is reasonable for most autonomous systems but can be improved for higher safety and responsiveness, especially in dynamic environments.

### 2.5.1 Detection Latency and Its Calculation

Detection latency is a measure of the time delay between when an input (e.g., sensor data) is captured and when the corresponding output (e.g., detection of lane boundaries) is produced. This is a critical factor for ensuring timely and accurate decision-making in self-driving cars.

### 2.5.2 Detection Latency Formula

Detection latency ($L_{\text{detection}}$) is calculated as the difference between the timestamp when the sensor data is captured ($T_{\text{capture}}$) and the timestamp when the lane markings or boundaries are detected and output ($T_{\text{detection}}$):

$$L_{\text{detection}} = T_{\text{detection}} - T_{\text{capture}}$$

### 2.5.3 Data Processing Pipeline

Detection latency can be further broken down into the following components:

- **Sensor Data Acquisition Time** ($L_{\text{acquire}}$): The time required to capture data from sensors such as cameras or LiDAR.
- **Data Processing Time** ($L_{\text{process}}$): The time required for feature extraction, machine learning model inference, and lane boundary prediction.
- **Post-Processing Time** ($L_{\text{post}}$): The time taken for any post-processing of detected lane boundaries.

The total detection latency is given by:

$$L_{\text{detection}} = L_{\text{acquire}} + L_{\text{process}} + L_{\text{post}}$$

### 2.5.4 Relating KPIs to Latency

While performance metrics such as Lane Marking Accuracy (LMA) and Lane Boundary Deviation (LBD) do not directly measure latency, they can correlate with latency under certain conditions:

- A high Lane Marking Accuracy (LMA) value may indicate that the system required more iterations or processing time to achieve accurate lane detection.
- A high Lane Boundary Deviation (LBD) value may suggest delays caused by inconsistent or inaccurate predictions of lane boundaries.

### 2.5.5 Experimental Derivation of Latency

To establish a relationship between KPIs and latency:

1. Measure the system's detection latency under controlled experimental conditions.
2. Log the corresponding LMA and LBD values during the tests.
3. Use statistical methods, such as regression analysis, to identify correlations between KPIs and latency.

### 2.5.6 Example Calculation

Let the following values be given:

$$\begin{aligned} L_{\text{acquire}} &= 10\,\text{ms}, \\ L_{\text{process}} &= 50\,\text{ms}, \\ L_{\text{post}} &= 20\,\text{ms}. \end{aligned}$$

The total detection latency is:

$$L_{\text{detection}} = L_{\text{acquire}} + L_{\text{process}} + L_{\text{post}} = 10 + 50 + 20 = 80\,\text{ms}.$$

Assume the following KPIs are observed:

$$\begin{aligned} \text{LMA} &= 363.90, \\ \text{LBD} &= 102.0. \end{aligned}$$

While these values do not directly calculate latency, trends in the data may reveal that higher LMA or LBD correlates with increased latency due to inefficiencies in the system. Regression analysis can be used to predict latency based on these KPI values.

### 2.5.7 Reducing Detection Latency

To minimize detection latency, consider the following optimizations:

- Use optimized sensor hardware for faster data acquisition ($L_{\text{acquire}}$).
- Implement lightweight and efficient machine learning models to reduce processing time ($L_{\text{process}}$).
- Simplify or optimize post-processing algorithms ($L_{\text{post}}$).

## 2.6 System Model and Data Flow

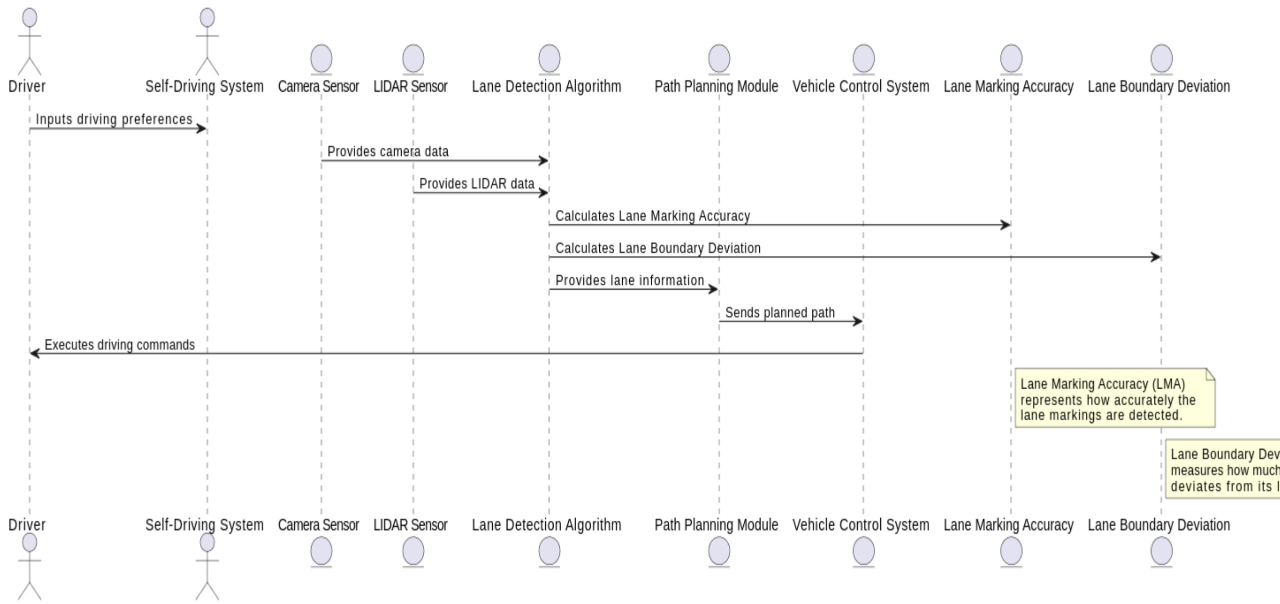
Below is the detailed explanation of the system's architecture and data flow:

- Sensors: Cameras, LiDAR, and Radar collect real-time data about the environment.
- Perception Module: This module processes sensor data to detect lane markings and boundaries, recognizing the road structure.
- Control System: Based on perception data, this system decides the necessary steering adjustments to keep the vehicle within the lane.
- Actuators: The steering actuator executes the control signals.

## 2.7 Latency and Performance Optimization

To improve detection latency, the system must minimize time spent in the processing pipeline. Faster image processing algorithms, optimized sensor fusion, and efficient control algorithms can significantly reduce the overall latency.

## 2.8 Diagrams and Visualizations




## 2.9 Conclusion

The self-driving car performs well in terms of lane marking accuracy but shows room for improvement in lane boundary deviation and latency. Reducing latency further would improve system responsiveness and safety, making it more suitable for real-time driving environments.