CSE495A

Introduction to Robotics

SECTION – 01

PROJECT REPORT

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Distance-Based Probability Modeling for Autonomous Overtaking Decisions on Double-Lane Highways Using Object Detection

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Abstract**: In this study, we propose a vision-based system for autonomous overtaking decision-making on double-lane highways, utilizing a small dataset comprising images collected from Kaggle and a few captured manually. The system employs image preprocessing techniques, including Gaussian blur and Canny edge detection, to enhance lane boundary segmentation via the Hough Line Transform. Leveraging the pretrained YOLOv3 object detection model, the system identifies and classifies objects within the driving lane. Distance to the nearest detected object is estimated using bounding box dimensions and a calibrated focal length. A probability-based safety model evaluates overtaking feasibility, dynamically scaling thresholds from unsafe (<10m) to optimal (>25m). This integrated approach provides real-time feedback on overtaking safety, addressing the obstacle avoidance challenge in autonomous driving.**

Keywords— Autonomous Vehicle (AVs), YOLO, Hough Line Transform, Gaussian Blur, Double Lane, Bounding Box

I. INTRODUCTION

The rise of autonomous vehicles (AVs) has spurred interest in advanced algorithms, sensors, and processors to enhance their functionality. AVs have the potential to transform transportation by reducing traffic congestion, improving safety, lowering urban emissions, and enhancing livability. By minimizing road accidents and addressing social, ethical, and technological challenges, they represent a significant step forward in mobility innovation [1]. Initially, AVs could handle only limited driving scenarios, but advancements in real-time data processing have made realistic, fully autonomous vehicles increasingly feasible [2][3].

Modern AV technologies, including computer vision, GPS, sensors, and mapping systems, are pivotal in detecting obstacles, assessing weather conditions, and determining optimal routes [4]. However, challenges remain in object detection and decision-making, particularly in complex environments like those found in Bangladesh. In such contexts, where unpredictable driving behaviors and inadequate infrastructure prevail, AVs must rely on real-time visualizations and robust decision-making algorithms to navigate safely and effectively.

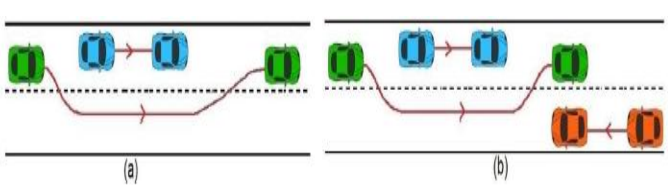

Fig.1. Diagram to visualize the dangers of overtaking in double-lane highway

A critical concern in this context is the risk of collisions during overtaking maneuvers. Fig.1 illustrates how a vehicle overtaking slower traffic on a two-lane road may inadvertently collide with an oncoming vehicle. This dangerous scenario arises when drivers misjudge the speed and distance of approaching vehicles or fail to return to their lane in time. Such incidents are especially prevalent on undivided roads common in countries like Bangladesh, where reckless overtaking often results in catastrophic accidents. Addressing this issue requires AV systems to accurately predict and respond to dynamic traffic conditions, ensuring safe overtaking decisions and minimizing the risk of collisions.

Because of this, road safety in Bangladesh is a pressing concern, with an alarming rise in traffic accidents and fatalities in recent years. According to the Bangladesh Road Safety Foundation's (RSF) 2021 annual report, 6,284 people died and 7,468 were injured in road accidents that year, an increase from 5,431 deaths and 7,379 injuries in 2020. Motorcycles accounted for 38.68% of all accidents in 2021, with 2,214 deaths and 1,309 injuries, marking a stark rise from 2020. Additionally, 927 women and 734 children perished in traffic accidents in 2021 [7]. Other contributing factors include reckless driving, overspeeding, forced overtaking, and hazardous road conditions. These statistics underscore the urgent need for improved road safety measures and advanced technologies to mitigate such incidents [8]. Autonomous vehicle technologies, particularly those focusing on object detection and decision-making, can play a significant role in addressing these challenges.

Convolutional neural networks (CNNs), particularly the YOLO model, are commonly used for object detection in AVs due to their ability to identify patterns in images efficiently. YOLO, a framework based on CNNs, processes images in patches, compressing them into vectors for faster learning and improved accuracy [5]. Given sufficient training data, YOLO models demonstrate excellent potential for object detection and segmentation, enabling AVs to make faster decisions, thus preventing accidents and improving safety [6].

II. RELATED WORKS

"Advancing Autonomous Navigation: YOLO-Based Road Obstacle Detection and Segmentation for Bangladeshi Environments"
Mahmud *et al.* conducted research focusing on enhancing autonomous vehicle navigation in Bangladeshi road environments by employing YOLO-based object detection and segmentation models. They utilized a custom-annotated

dataset of images derived from videos capturing diverse road conditions, including potholes, speed bumps, and varying weather and lighting scenarios. Through the application of YOLOv5, YOLOv7, and YOLOv8 models, their experiments revealed that the YOLOv5x model achieved the highest performance with mAP50 and mAP50-95 scores of 0.876 and 0.647, respectively, while YOLOv7x yielded the lowest performance. The research demonstrated improved results when comparing models trained on the custom dataset versus a benchmark dataset. By deploying these models in a real-time prototype, the study showcased the feasibility of achieving effective and resource-efficient obstacle detection, particularly addressing the infrastructural challenges unique to developing nations [9].

“Object and lane detection for autonomous vehicle using YOLO V3 algorithm”

Object detection is essential for autonomous vehicle safety, enabling real-time navigation and decision-making. Mohanapriya *et al.* proposed using the YOLO V3 algorithm for detecting objects such as vehicles, pedestrians, and traffic lights, along with lane detection, through a camera mounted on a moving vehicle. This approach overcomes the limitations of earlier methods like CNNs with ResNet-50, which relied on fixed cameras and could not detect lanes and objects simultaneously. YOLO V3's superior accuracy, feature extraction, and large-scale detection capabilities make it highly effective for autonomous systems [10].

“Lane Detection in Autonomous Vehicles: A Systematic Review”

Emphasizing their pivotal role in Advanced Driver Assistance Systems (ADAS) for ensuring passenger and driver safety in autonomous vehicles, Zakaria et al. conducted a comprehensive review of lane detection methods. Their study analyzed 102 publications from 2018 to 2021, categorizing approaches into geometric modeling, traditional methods, and artificial intelligence-based techniques such as deep learning and machine learning. Notably, deep learning emerged as the dominant approach, often combined with attention mechanisms or classical methodologies, showing promising outcomes in lane detection. The review highlighted challenges, including accuracy, speed, and adaptability to extreme conditions, and stressed the importance of improving performance to advance autonomous vehicle technologies. This aligns with recent research by S. Mohanapriya et al., who explored YOLO-based lane and object detection techniques, reinforcing the growing trend of employing deep learning for enhanced navigation capabilities [11].

“Autonomous vehicular overtaking maneuver: A survey and taxonomy”

Lodhi *et al.* provide a comprehensive review of autonomous vehicular overtaking maneuvers, emphasizing their critical role in improving driving precision, fuel efficiency, and overall safety while addressing challenges like traffic complexity and technical compatibility. Overtaking is identified as one of the most intricate maneuvers compared to lane changing or following, requiring advanced strategies to ensure traffic safety and operational efficiency. The study categorizes existing overtaking methods into theoretical and AI-based approaches, presenting taxonomy, simulators, and applications tailored to this task. By highlighting research gaps and proposing future directions, the survey serves as a foundational resource for advancements in autonomous vehicle overtaking systems [12].

“Implementation of an Autonomous Overtaking System Based on Time to Lane Crossing Estimation and Model Predictive Control”

Lin *et al.* proposed a robust autonomous overtaking system that integrates time to lane crossing (TLC) estimation and model predictive control (MPC) to enhance overtaking safety and efficiency in autonomous vehicles. The system utilizes a vision-based lane-detection method for accurate TLC estimation, enabling timely overtaking decisions. Additionally, a successive linearization-based MPC optimizes vehicle control, such as throttle, brake, and steering, while ensuring safety by maintaining proper longitudinal acceleration and steering velocity. The approach was validated through real-world experiments on a prototype electric golf cart, demonstrating its capability to handle complex driving scenarios, including lane-following and overtaking with varying vehicle dynamics [13].

III. DATASET DESCRIPTION

Fig.2. Four Random images of double-lane highway roads from a car’s POV

For this project, we collected a dataset from two main sources: Kaggle [15] and custom images captured on roads in Bangladesh. The initial Kaggle dataset contained approximately 3,000 images, but 90% of them were from urban roads, which did not align with our focus on overtaking maneuvers. Since overtaking accounts for 4-10% of traffic accidents, particularly on double-lane highways, it is crucial to focus on environments where overtaking is more feasible [14]. City roads, often congested and with dividers, are less relevant for this study.

To address this, we selected 25 images from the Kaggle dataset depicting highway conditions suitable for overtaking scenarios. Additionally, we included 10-11 custom images captured along the Dhaka to Mawa highway, which were originally taken during our 499A course but were later found useful for studying overtaking on double-lane highways.

In total, the dataset consists of around 35 images, some shown in Fig. 2, representing various conditions on double-lane highways in Bangladesh, which will be used for developing and evaluating our overtaking detection algorithm.

IV. PROPOSED METHODOLOGY

A. Pre-Trained YOLOv3

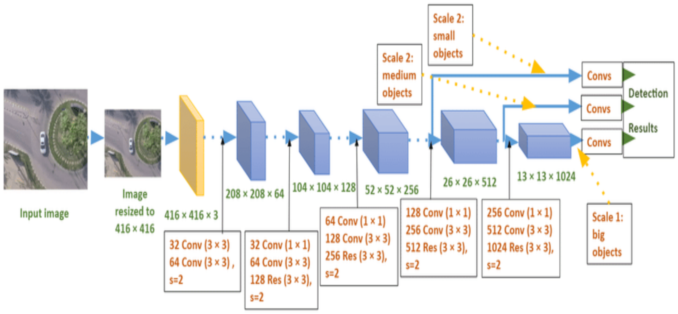

Fig.3. YOLOv3 Architecture Diagram

To start, we evaluated our dataset using a pre-trained YOLOv3 (You Only Look Once, version 3) model from [16], which provides bounding boxes around detected objects, along with confidence scores for each prediction. The model was loaded along with the COCO class labels to detect objects such as cars, pedestrians, trucks, etc. The image was first resized to 416*416 pixels. Then after forwarding it, YOLOv3 provides output for bounding boxes, class predictions, and confidence scores:

$$Confidence\ score = P(object) * P(class|object)$$

Bounding Box(x, y):

$$x = center_x - \frac{width}{2},\ y = center_y - \frac{height}{2}$$

Fig.4. Random image output from YOLOv3 model

B. Segmentation and Filter Preprocessing Techniques

YOLOv3 detected objects however, objects outside the double-lane highway, such as pedestrians on the roadside, were also detected, which are irrelevant to our goal of analyzing the overtaking scenario on highways. To exclude them, we introduced segmentation and filtering techniques. Specifically, lane detection was performed using edge detection (Canny) and Hough Line Transformation to identify the region of interest (the double-lane area).

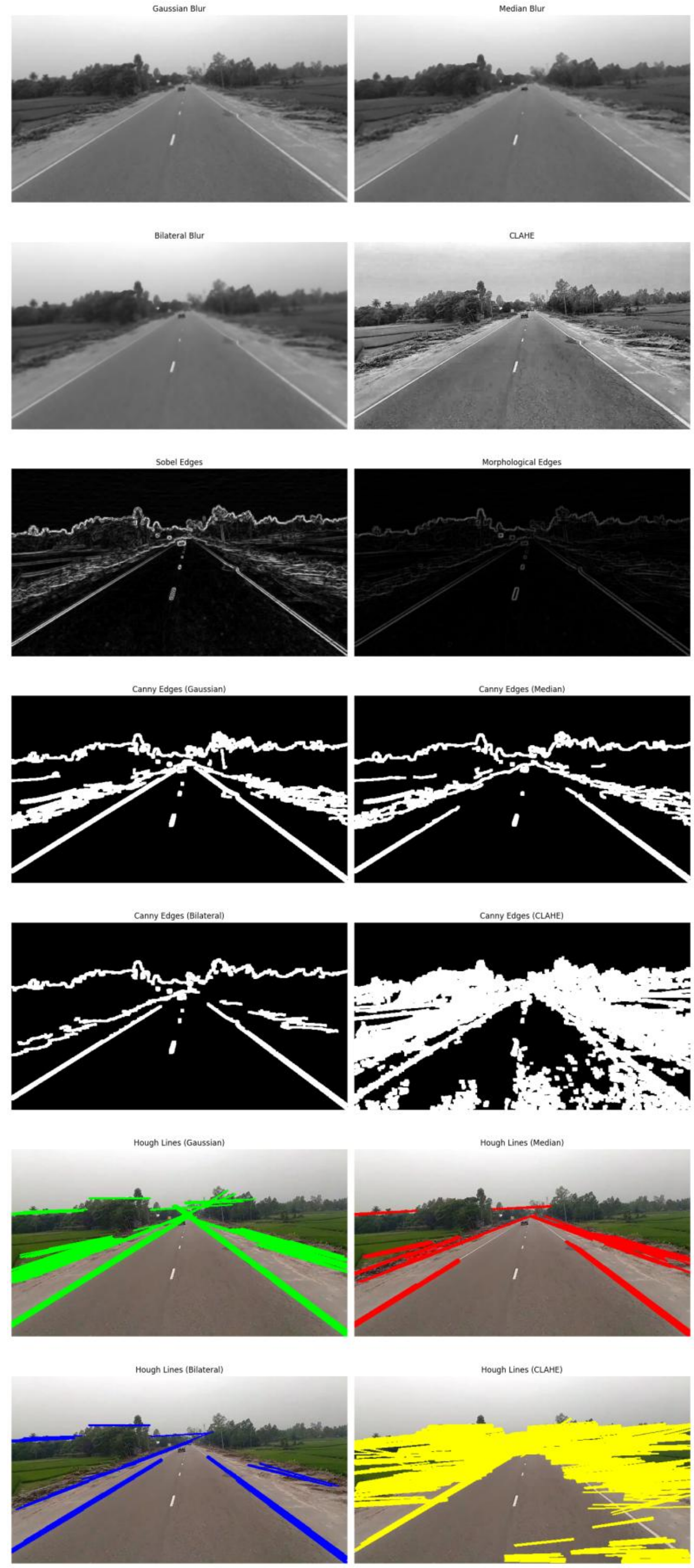

Fig.5. Segmentation and Filter Techniques: ['Gaussian Blur', 'Median Blur', 'Bilateral Blur', 'CLAHE', 'Sobel Edges', 'Morphological Edges', 'Canny Edges (Gaussian)', 'Canny Edges (Median)', 'Canny Edges (Bilateral)', 'Canny Edges (CLAHE)', 'Hough Lines (Gaussian)', 'Hough Lines (Median)', 'Hough Lines (Bilateral)', 'Hough Lines (CLAHE)']

Several preprocessing techniques were applied to enhance edges and suppress noise to see if our model can focus only on the "regions of interest".

We used several filtering methods for edge detection to smoothen our image:

- **Median Blur:** Removes salt-and-pepper noise by replacing pixel values with the median of their neighbors
- **Bilateral Filtering:** Reduces noise while preserving edges by weighting pixel values based on spatial and intensity proximity
- **Gaussian Blur:** Smoothens the image by averaging nearby pixel intensities

$$Gaussian\ Blur, G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Then, we used several edge detection algorithm techniques of which we observed Canny Edge to work best on Gaussian Filtered images to extract best edges of lane regions. It involves gradient calculation where intensity gradients, (G_x, G_y) are calculated using operators like Sobel or Prewitt and identifies strong edges and weak edges using two thresholds, (T_{high}, T_{low}). Gradient calculation:

$$G = \sqrt{G_x^2 + G_y^2}\ ,\ \ \theta = \tan^{-1}(\frac{G_y}{G_x})$$

After detecting the edges, we apply Hough Line Transformation to detect straight lines on the Canny Edge map by transforming points into the Hough space:

$$\rho = x\cos\theta + y\sin\theta$$

Fig.6. YOLOv3 output before and after preprocessing techniques applied

As you can see in Fig.6, now the model is excluding the objects in the side lanes, ensuring that only objects within the highway lanes are detected and considered for decision-making. This focused detection significantly enhances the model's relevance and accuracy in scenarios such as determining safe overtaking conditions.

C. Distance Estimation for Overtaking Decision

The next crucial step is estimating the distance of detected objects within the lane. This helps determine if overtaking is feasible and safe. Using the bounding box height, the distance of an object is inversely proportional to its apparent height in the image, assuming a known real-world height of the object and a calibrated camera focal length. The formula for distance estimation is:

$$d = \frac{H_{real} * f}{H_{image}},$$

$where,$

d: $Estimated\ distance\ to\ the\ object,$
H_{real}: $Real\ world\ height\ of\ the\ object$ (e.g., 1.5 meters for a car),
f: $Focal\ length\ of\ the\ camera$ (calibrated; here assumed as 800 pixels),
H_{image}: $Height\ of\ the\ bounding\ box\ in\ the\ image$ (in pixels).

Using this formula, we calculated the distance for each object detected within the lane region as shown in Fig.7.

Fig.7. Value of estimated distance of each detected object in lane region is shown

V. RESULT ANALYSIS

We analyze the results of our overtaking decision-making system and provide insights into a custom probability calculation method we made to determine overtaking safety. The threshold values used in the overtaking probability calculation are entirely based on assumptions made by us, the researchers. These values were chosen based on logical reasoning and preliminary observations. However, they have not been verified in real-life conditions. If this project is extended on a larger scale, we plan to conduct real-world testing and fine-tune these thresholds for improved accuracy and reliability.

The overtaking probability is determined using the following logic:

1. **Very Close Distances ($d < 2\ meters$):** Overtaking is deemed extremely unsafe in this range, with a probability fixed at **15%**.
2. **Moderate Distances ($2 \le d < 10\ meters$):** The probability increases linearly as the distance increases, representing a transition from unsafe to moderately safe. Suppose the distance of object is 3m, then the formula used is:

$$P = \frac{d-2}{8} * 65 + 15$$

$$P = \frac{3-2}{8} * 65 + 15 = 23\%$$

Here, the probability smoothly transitions from **15%** to **80%.**

3. **Safe Distances ($10 \le d < 25$ meters):** For distances within this range, overtaking is considered safer. The probability increases linearly from **80%** to **100%.** Suppose the distance now for closest object is 18m, then the formula is:

$$P = \frac{d - 10}{15} * 20 + 80$$

$$P = \frac{18 - 10}{15} * 20 + 80 = 90\%$$

4. **Very Safe Distances ($d \ge 25$ meters):** At this range, overtaking is deemed fully safe, with the probability fixed at **100%.**

Fig.8. Two random output results of both "Can overtake" and "Cannot overtake" cases

The overtaking decision displayed in Fig.8 is based on the calculated probability:

- **"You can overtake"** is shown when the probability exceeds **80%.**
- **"You cannot overtake"** is shown when the probability is **80% or lower.**

VI. LIMITATIONS AND FUTURE WORKS

Limitations

- Due to insufficient time, we could not train the YOLOv3 model on highway lane images specific to Bangladeshi standards. This was one of our primary goals, as it would have significantly improved the system's accuracy in detecting lane regions and vehicles in local contexts.
- The current distance estimation is a simplistic approach. A more robust approach, such as using SLAM (Simultaneous Localization and Mapping) techniques, could have been employed. However, this would require a video dataset for more accurate localization and depth perception.
- Speed measurement of incoming vehicles is not implemented, as we focused on single-image processing rather than videos. Incorporating this feature would have provided additional safety metrics for overtaking decisions.

Future Works

- Developing a dataset of Bangladeshi highways and training the YOLOv3 model on these images will enhance detection accuracy for regional traffic scenarios.
- Implementing SLAM techniques for distance calculation will significantly improve accuracy, as it takes into account real-time localization, object motion, and depth mapping [18]. A video dataset would be necessary for this enhancement.

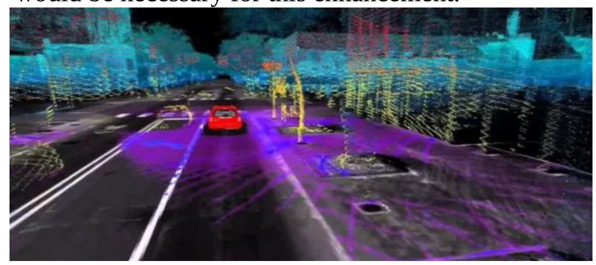
Fig.9. Localization and mapping using SLAM technique

- By using a video dataset, we can calculate the speed of detected vehicles. This information, combined with distance, could further refine overtaking probability calculations.
- Inspired by Samsung's display truck concept [17], which shows the frontal view of the road on a rear display to assist overtaking, we propose a simpler solution: adding LED displays to vehicles. These displays could show messages like **"You can overtake"** or **"You cannot overtake"** based on the system's analysis. This approach is cost-effective compared to a full display with similar functionality.

Fig.10. Samsung's concept V/S Our concept

- Introducing a custom overtaking algorithm like the one proposed in [13] could enhance decision-making. The algorithm uses reference points and constraints, along with Model Predictive Control (MPC), to determine the optimal overtaking strategy. While complex, this algorithm could be implemented in a later stage for more precise overtaking predictions.

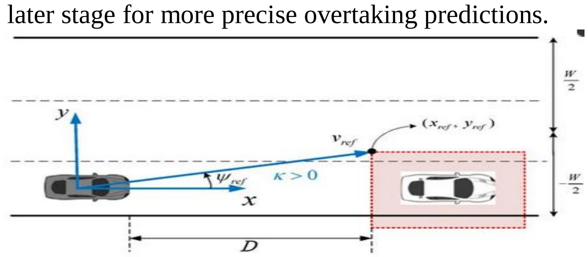

Fig.11. Proposed Overtaking Control Algorithm Diagram in [13]

- The system could be extended by integrating advanced sensors like LiDAR and radar for enhanced object detection and distance estimation in real-world driving conditions [20].
- Developing a real-time implementation of this project on embedded hardware, such as Raspberry Pi or NVIDIA Jetson Nano, would allow direct integration into vehicles [19].
- Extending the system to provide other safety features, like lane departure warnings, collision avoidance, and driver behavior analysis, could increase its utility.
- Finally, real-world testing on highways with diverse environmental conditions (e.g., rain, fog, low-light scenarios) is essential. Such testing will provide feedback to refine the thresholds, algorithms, and decision-making logic.

By incorporating these improvements and extensions, this project could be developed into a reliable and scalable system for real-world deployment, providing a significant contribution to road safety and autonomous driving technologies.

VII. CONCLUSION

In overall, we successfully developed a system that leverages YOLOv3 for object detection and calculates overtaking probabilities based on distance estimation, aiming to enhance road safety. While we were able to implement key components, including lane region detection and basic overtaking analysis, we were unable to train the model with a Bangladeshi highway dataset due to time constraints. Future work will focus on improving distance estimation through SLAM, integrating vehicle speed measurements, and expanding the system to include real-time displays for vehicles. Additionally, we plan to explore advanced algorithms and large-scale testing to refine the system for practical deployment.

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