Image Processing Project

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***Abstract*—Lane-keeping and lane-changing systems are critical components of modern autonomous driving technologies. These systems rely on image processing techniques to detect lane boundaries, track vehicle position, and enable safe lane transitions. Traditional approaches based on edge detection and Hough transform often struggle under complex road conditions. Recent advancements in deep learning, particularly convolutional and recurrent neural networks, have significantly improved lane detection accuracy and robustness. This paper reviews key research contributions in the field, focusing on sensor-based lane detection, deep learning-driven lane-keeping, lane change recognition, and event-based vision techniques. By analyzing these works, we highlight current state-of-the-art methodologies and identify potential areas for further enhancement in autonomous navigation.**

***Index Terms*—Lane detection, lane-keeping, lane-changing, autonomous vehicles, image processing, deep learning, convolutional neural networks (CNNs), recurrent neural networks (RNNs), event-based vision, computer vision.**

I. INTRODUCTION

With the rise of autonomous driving technologies, lane-keeping and lane-changing systems have become crucial components of modern intelligent transportation. These systems rely heavily on image processing techniques to detect lane boundaries, track vehicle position, and make real-time decisions for safe navigation. A robust lane-keeping system ensures that a vehicle remains centered in its lane, while a reliable lane-changing algorithm allows for safe and efficient lane transitions.

Traditional lane detection methods utilize edge detection and Hough transform techniques to identify lane markings. However, these methods often struggle in complex road conditions, such as poor lighting, occlusions, and worn-out lane markings. Recent advancements in computer vision and deep learning have introduced more robust approaches, leveraging convolutional neural networks (CNNs), recurrent neural networks (RNNs), and event-based vision sensors to enhance lane detection and control accuracy. These advanced methodologies not only improve lane detection under varying environmental conditions but also enable predictive modeling for vehicle trajectory estimation and decision-making processes.

The implementation of image processing for lane-keeping and lane-changing is further enhanced by real-time processing techniques that optimize computational efficiency. The integration of multiple sensor modalities, such as LiDAR, radar, and cameras, has provided a more holistic approach to lane detection. However, the reliance on image-based processing remains a critical component due to its cost-effectiveness and high-resolution data capture.

This literature review explores key research contributions in the field of lane-keeping and lane-changing systems using image processing. The selected studies focus on different methodologies, including sensor-based lane detection, deep learning-driven lane-keeping, lane change recognition, and event-based vision techniques. By analyzing these works, we gain insights into the current state-of-the-art approaches and identify potential areas for further improvement in autonomous navigation. Additionally, we discuss the limitations of existing methods and propose potential future research directions to enhance the robustness and adaptability of lane detection and control systems.

II. LITERATURE REVIEW

A. Lane Detection and Control

One of the fundamental tasks in lane-keeping systems is detecting lane boundaries accurately. The work by [1] presents a cost-effective image sensor processing technique for lane detection and control. The study proposes an efficient algorithm that enhances lane detection accuracy, reducing computational overhead for real-time applications. The authors leverage image filtering and segmentation techniques to extract lane markings and ensure robust performance under varying lighting conditions.

B. Lane Change Assistance

To ensure safe lane-changing, a robust lane detection and blind-spot detection system is crucial. The research by [2] develops a rearview camera-based lane change assistance system utilizing convolutional neural networks. The model enhances situational awareness by detecting blind spots, allowing for more accurate lane-change decisions. The paper further explores the effectiveness of CNNs in real-world driving scenarios and compares performance metrics with traditional vision-based approaches.

C. Deep Learning for Lane Keeping

Recurrent neural networks (RNNs) have been applied in lane-keeping models to improve vehicle trajectory prediction. The study in [3] integrates lane marker detection with RNNs to develop an interactive lane-keeping model, considering surrounding vehicles to optimize steering control. The proposed system incorporates temporal dependencies in lane detection, improving tracking accuracy across consecutive frames. The paper also highlights the potential of reinforcement learning techniques in refining lane-keeping strategies based on real-time feedback.

D. Lane Change Behavior Recognition

A deep residual neural network-based approach is proposed by [4] to detect lane-changing behavior using vision-based methods. The research demonstrates high accuracy in predicting lane changes, highlighting the importance of image processing in recognizing vehicle maneuvers. The study evaluates different network architectures and assesses their generalization capability across various road conditions. Additionally, it discusses the integration of sensor fusion techniques to enhance robustness in lane-change recognition.

E. Event-Based Lane Marking Detection

Recent advancements in event-based vision sensors have led to improved lane detection systems. The study by [5] introduces LDNet, an end-to-end lane marking detection model leveraging a dynamic vision sensor. The approach achieves higher accuracy compared to conventional frame-based lane detection methods. The research discusses the advantages of event-based vision in reducing motion blur and improving detection speed, making it a promising alternative for high-speed autonomous driving applications.

III. Project Hardware

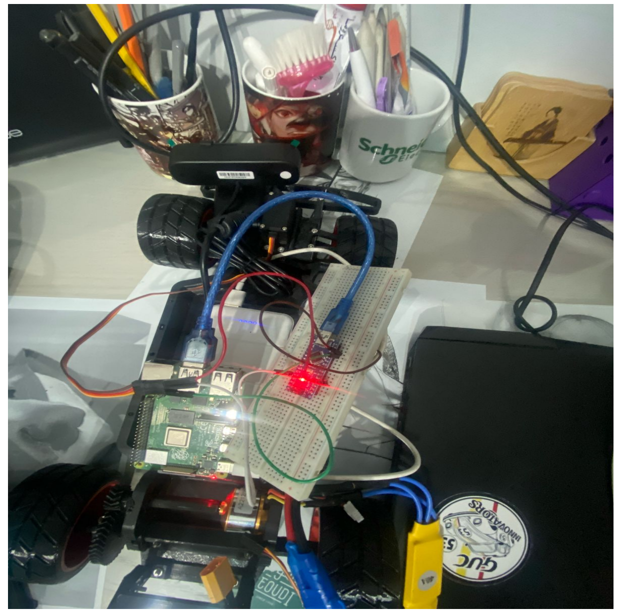

Fig. 1. project hardware

As we can see in the image the raspberry pi is connected to the laptop via wifi and connected to arduino via cable to communicate with it using pyserial and the arduino sends to the servo the actuating signals.

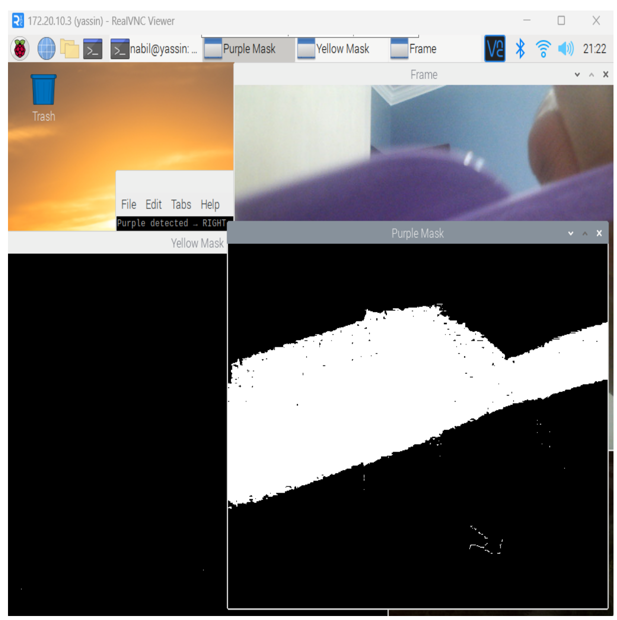

Fig. 2. Purple mask

This image shows that when the camera detects purple color the pi sends command to arduino so that arduino sends to the servo to go right.

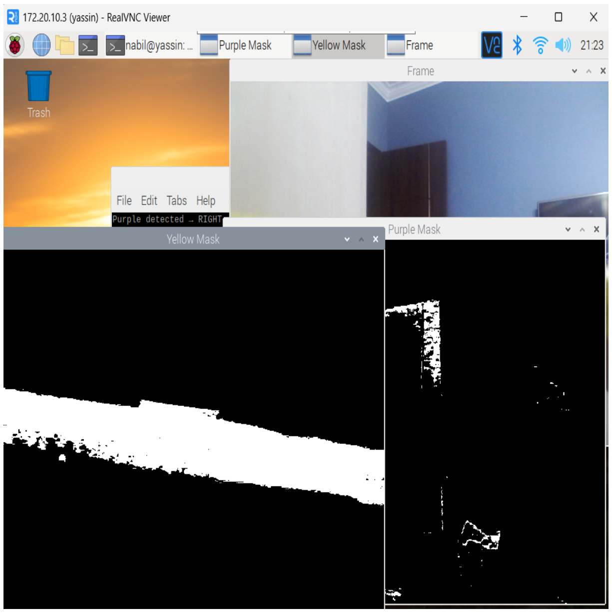

Fig. 3. Yellow mask

In this image it is shown that when the camera detects yellow color it sends command to arduino to make the servo motor go left.

This operation was done twice once on the raspberry pi and once on the pc and it was observed that when operated on the pc it was much faster than the pi.' '

IV. Closed Loop Response

In this section we are going to elaborate on how we process the image so that it is execute the required function from our project.

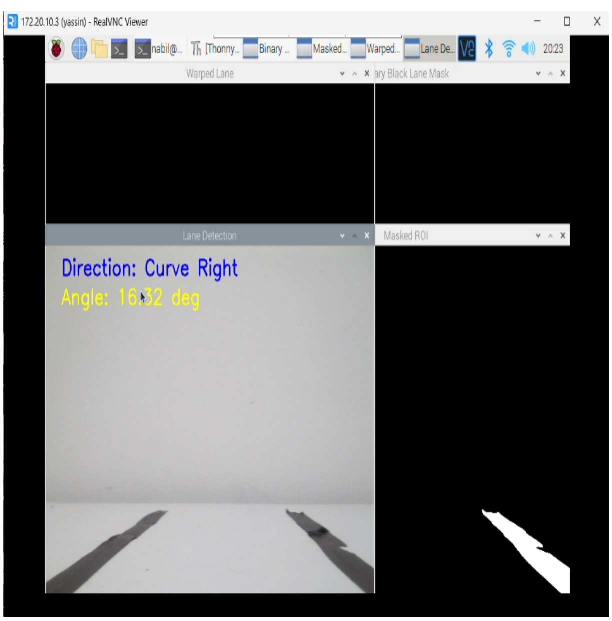

Fig. 4. The image processing

we could not develop a full track with lanes so for the sake of this mile stone we just rotated the camera on the same lane in order to observe change on the servo angle.

In Fig. 4. It is shown the original image, but we are tilting the camera a little to the left so that it sees the lane going to the right.

However, what the code basically do is capture the original image then it warps the image so that it makes the lane parallel to each other from the camera view instead of looking like a trapezoid then it convert it to binary image then gets the X and Y (position) of each white pixel in the image then it does on all the points it gathered polynomial fighting using NP library. We used polynomial fitting hoping that it will be better at detecting curves.

After the fitting is done and the coefficient of the polynomial is computed from them we calculate the steering angle for the servo by averaging the two polynomials we got into a polynomial in the middle for the car to follow by computing it's tangent and from the tangent we compute the slope which is approximately the steering angle. Which is then sent to the servo.

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