Lane Marker Detection

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Abstract: This concise abstract presents a Detection of Lane Markers project executed using the Hough Transform technique in Python. In this study, we address the task of robustly detecting lane markers on roadways, a crucial component of autonomous driving systems. The primary aim of our work is to enhance road safety and aid in the development of self-driving vehicles. Our investigation utilizes the Hough Transform method, a powerful tool for identifying lines and shapes within an image. Through rigorous experimentation and algorithm tuning, we have achieved remarkable results in lane marker detection accuracy. This project uses open-source Python libraries and is easily adaptable for real-world applications. The value of our work lies in its potential to contribute to safer and more efficient transportation systems, reducing the risk of accidents and increasing the reliability of autonomous vehicles. By accurately identifying lane markers, our system enhances lane-keeping capabilities and fosters a safer driving environment. In conclusion, our Lane Marker Detection project, implemented using Hough Transform in Python, presents a promising approach for improving the safety and reliability of autonomous driving systems.

1. Rezumat in limba romana/Summary in an European language

Proiectul se concentrează pe implementarea unei metode de detectare a marcajelor rutiere în imagini utilizând transformata Hough. Algoritmul utilizează tehnici precum detecția marginilor Canny și transformata Hough pentru identificarea liniilor asociate marcajelor pe șosea.

Acest proces implică transformarea imaginii într-o reprezentare Hough, unde punctele care corespund liniilor din imagine sunt evidențiate într-un spațiu Hough. Apoi, se identifică dreptele din această reprezentare, corespunzătoare marcajelor rutiere, și sunt evidențiate în imaginea originală. Acest proces oferă o metodă robustă și eficientă de detecție a liniilor de pe carosabil, esențială în domenii precum asistența la conducere sau interpretarea automată a imaginilor din trafic.

O regiune de interes (ROI) este definită pentru a concentra atenția asupra zonei relevante a imaginii, în general, zona carosabilului. Această regiune este aplicată ca o mască pentru a elimina informațiile irelevante din detecția ulterioară a liniilor.

Transformata Hough este utilizată pentru a identifica liniile în imaginea procesată. Prin aplicarea acestei transformate, se identifică parametrii liniilor în spațiul Hough, permițând reprezentarea acestora sub formă de perechi de coordonate (panta, intersectarea cu axa y). Aceste informații sunt apoi folosite pentru a evidenția liniile detectate pe imaginea originală.

Rezultatul final constă în evidențierea liniilor detectate pe imaginea originală, furnizând astfel informații despre direcția și poziționarea acestor linii de marcaj. Algoritmul poate fi ajustat prin tunarea parametrilor, inclusiv cei utilizați în transformata Hough și în metoda Canny, pentru a se potrivi mai bine condițiilor specifice ale imaginilor și a asigura o detecție precisă a marcajelor de bandă în contexte variate de iluminare și pe diferite tipuri de drumuri.

2. State of the Art

In the exciting field of image processing for lane marker detection, current advancements are focused on improving the precision and efficiency of systems. Deep learning, especially Convolutional Neural Networks (CNNs) (as presented in [AlMamun21]), has taken centre stage to enhance the accuracy of recognizing lane markings under various road conditions.

Within the dynamic field of lane marker detection, the evolution of image processing algorithms has transcended traditional techniques such as the Hough Transform. Noteworthy progress in recent years includes the probabilistic Hough Transform, building upon the conventional method by Galamhos, Matas, and Kittler [Galamhos99]. This probabilistic approach enhances line detection in scenarios where lines may be fragmented or challenging to discern, proving particularly effective in handling noisy data, and contributing to improved accuracy in identifying lane boundaries.

Algorithms incorporating adaptive thresholding dynamically adjust sensitivity based on local image content. Ding, Lee, and Lee's adaptive Region of Interest (ROI) determination algorithm [Ding13] dynamically focuses on relevant image portions, improving adaptability to changing road conditions.

The advent of deep learning, exemplified by architectures like SegNet [AlMamun21], has revolutionized lane marker detection. Allowing convolutional layers to automatically learn hierarchical features, deep learning-based approaches eliminate the need for handcrafted features, enhancing accuracy in complex scenarios with varying road conditions.

With the advent of video-based systems, McCall and Trivedi [McCall06] conducted a comprehensive survey, system development, and evaluation for video-based lane estimation and tracking. Their work contributed significantly to the transition from image-based to video-based lane marker detection systems.

Lane marker detection has witnessed a remarkable evolution, from classical methods like the Hough Transform to the latest advancements in deep learning. The integration of adaptive algorithms and video-based systems has significantly improved the robustness of lane detection systems. The adoption of deep learning techniques, exemplified by SegNet, represents a paradigm shift towards more efficient and accurate solutions. As researchers continue to explore innovative approaches, the future holds promising developments in making lane marker detection an even more integral part of autonomous driving and driver assistance systems.

3. Theoretical Fundamentals

The Hough Transform is a mathematical technique used to identify geometric shapes within an image. In the context of lane marker detection, the Hough Transform is particularly valuable for detecting straight lines. It works by representing each point in an image as a set of parameters in a transformed space, often referred to as the Hough parameter space.

Utilizing the Hough Transform (HT) to detect lines in an image involves computing the HT for the entire image, accumulating votes in an array, and then identifying peaks in the array to reveal potential lines in the input image.

The first step is to transform the input image using Duda's modified Hough Parametrization (HP) [Duda72], which represents lines using two key parameters: the length of the normal (ρ) to the line and the angle (θ) that this normal makes with the x-axis, as specified by equation (1).

$$\rho = x cos\theta + y sin\theta \qquad (1)$$

The locus of points corresponding to (x, y) constitutes a sinusoidal curve and all the cells along it receives votes.

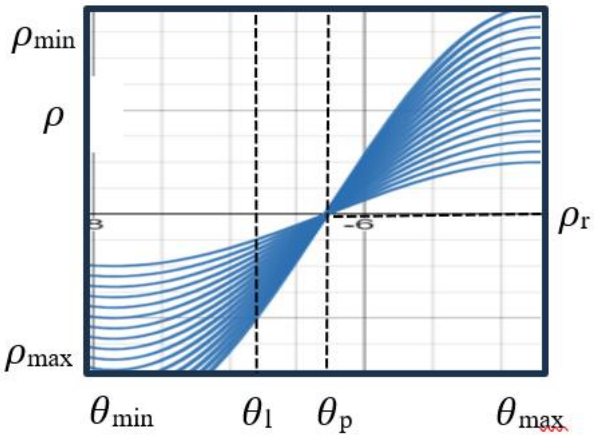

Figure 1- Distribution of votes

Accumulations of votes are called peaks, like the one at (ρ_r, θ_p). The process of peak formation describes a butterfly shaped spread of votes. The spread of the entire line segment is bound by the votes of the end points.

Within the Hough space, peaks serve as indicators of potential lines or patterns present in the image. These peaks, as local maxima, signify regions with robust evidence of underlying structures.

Each peak's position in the Hough space precisely corresponds to the (ρ, θ) parameters characterizing a detected line in the image space. Subsequently, these (ρ, θ) values are meticulously transformed back into Cartesian coordinates, facilitating the retrieval of actual lines or shapes existing within the image. This intricate process allows for the accurate identification and representation of the image's structural components.

4. Implementation

In the initial stage of the project, the input image is loaded using the OpenCV library, and its dimensions, namely height and width, are determined through the shape attribute of the image array.

Following this, a trapezoidal region of interest (ROI) is defined to focus specifically on the area of the image where lane markers are expected. The vertices of this trapezoid are calculated based on the image dimensions and adjusted accordingly.

The lane detection process begins with preprocessing the image. This involves converting it to grayscale, applying Gaussian blur to reduce noise, and utilizing the Canny edge detection algorithm to identify edges. The resulting edges are then masked within the previously defined ROI, narrowing the focus to the relevant portion of the image.

For line detection, the Hough Transform algorithm is employed, yielding a set of lines represented by their endpoints (x1, y1, x2, y2) in the image.

Following line detection, slopes and intercepts are calculated for each line, categorizing them into left and right lanes based on their slopes. The averages of slopes and intercepts are then computed separately, and extended lines are created using these averaged parameters to represent the detected lane boundaries.

To visually highlight the detected lines, a black image is created, and the averaged lines are drawn on it. The original image and the line-highlighted image are combined using the addWeighted function from OpenCV.

The final processed image, showcasing the highlighted lane lines, is displayed using Matplotlib. Additionally, the resulting image is saved as "final_image.jpg" for further analysis or reference.

This detailed implementation provides a comprehensive overview of the lane marker detection process, from image loading to the visualization of the final output, offering insight into the core components of the algorithm, and serving as a foundation for further enhancements and adaptations.

5. Experimental Results

After conducting numerous experiments to assess the algorithm's performance across various images, we have achieved satisfactory results. The subsequent sections will outline the intermediate steps and outcomes of our implementation (see Fig2 to Fig7).

An important advantage of the algorithm is that the pixels on the lines are not required to be contiguous. It is effective when viewing the lines with small gaps due to noise or when they're partially obstructed. Thus, Hough Transform is an excellent tool when noise immunity is required.

Furthermore, using the "Canny edge" feature the Hough transform can select the lines from the unnecessary background information. Then the lines with marginal slope difference will be square fitted so that we obtain clearer straight lines.

The Hough Transform, though adept at detecting straight lines, presents challenges for lane marker detection due to sensitivity to parameter tuning, computational intensity, vulnerability to noise, limited handling of curved lanes, sensitivity to lighting conditions, dependency on accurate edge detection, and difficulty in generalizing to complex scenes. Addressing these issues requires additional techniques for robust and accurate performance in real-world scenarios.

Consider improving the lane marker detection code by incorporating deep learning techniques like Convolutional Neural Networks (CNNs) (as presented in [AlMamun21]). By training the model on diverse road images, CNNs can enhance feature extraction and predict lane boundaries more accurately, offering increased adaptability and robustness in challenging conditions such as low light or complex road geometries. This shift to deep learning may involve additional preprocessing steps but can result in a more effective and flexible lane marker detection system.

Figure 2- Input image

Figure 3- Gray scale image after Gaussian blur

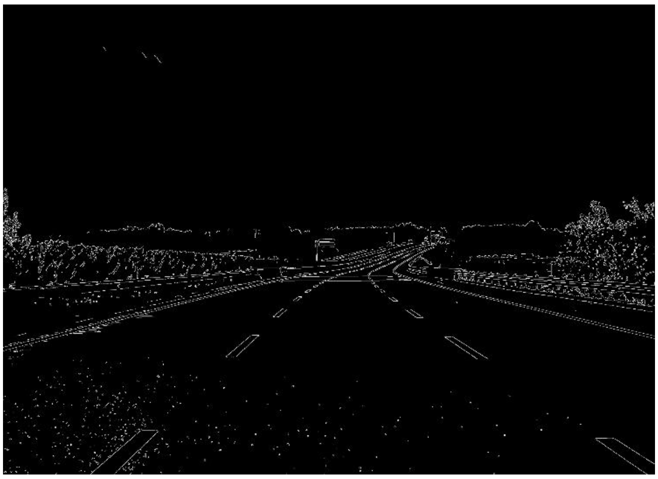

Figure 4- The image after Canny edge detection

Figure 5- Masked image

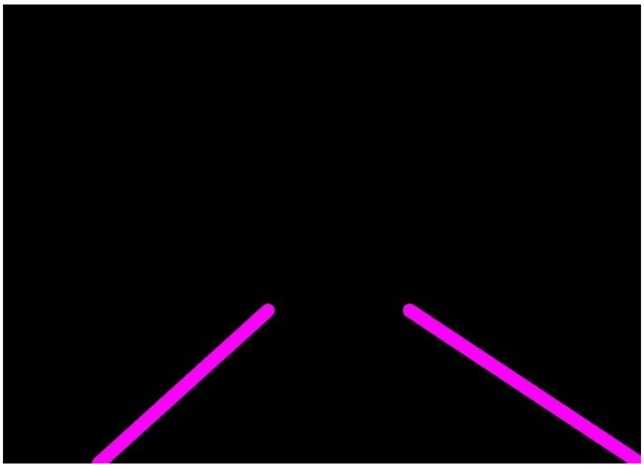

Figure 6- Lines detected.

Figure 7- Final image

6. Conclusions

In conclusion, the Lane Marker Detection project, employing the Hough Transform, stands as a critical component in advancing computer vision applications for autonomous driving and driver assistance systems. The Hough Transform method provides an effective means to identify and extract lane markers from complex and noisy images, contributing to the overall goal of ensuring safe and reliable vehicle navigation.

Future improvements could involve refining the algorithm's response to challenging conditions and exploring simple enhancements. Overall, the project's success lies in its contribution to fundamental lane detection for applications in basic driver assistance systems.

7. References

7.1 Journal articles

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13.7 Thesis