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Vehicle Detection and Counting based on Digital Image Processing

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ABSTRACT: The detection of vehicles plays a crucial role in the improvement and expansion of road infrastructure. Data gathered from traffic monitoring aids in budget planning for road maintenance. Traffic monitoring can be conducted either manually, involving human labour to count and record vehicles using tally sheets, or automatically. The manual method is prone to human error. Most current automatic traffic census systems utilize magnetic loop detectors, which are expensive and non-removable once installed. Therefore, there is a need for a system that can automatically detect and count vehicles without relying on human labour or expensive equipment. This work proposes the use of simple cameras to achieve vehicle detection and counting.

KEYWORDS: Vehicle detection, Vehicle counting, Background subtraction, Canny edge detection, Kalman filter.

I. INTRODUCTION

Vehicle detection and counting using digital image processing have become critical components of modern traffic management systems, providing valuable data for optimizing traffic flow, enhancing road safety, and reducing congestion. In recent years, advancements in image processing and machine learning algorithms have significantly improved the accuracy and efficiency of these systems. However, as urban environments become more complex and dynamic, new challenges have emerged that necessitate further innovation. This research aims to address the evolving obstacles in vehicle detection and counting by exploring advanced methodologies and technologies that can enhance system performance in diverse and challenging conditions.

One of the primary challenges faced in 2024 is the increased traffic density in urban areas, which complicates vehicle detection due to occlusion and overlapping vehicles. Additionally, the rise of diverse vehicle types, including electric vehicles, autonomous vehicles, and micro-mobility devices, demands more sophisticated classification algorithms to accurately identify and differentiate between these various modes of transportation. Adverse weather conditions and low-light environments further degrade the performance of traditional detection systems, while limitations in edge computing resources pose challenges for real-time processing. This research paper will investigate these issues in detail and propose solutions leveraging advanced image processing techniques, such as Kalman filters and Canny edge detection, to enhance the reliability and accuracy of vehicle detection and counting systems in the face of these modern challenges.

II. RELATED WORK

The field of vehicle detection and counting has seen significant advancements, leveraging various technologies to enhance the accuracy and efficiency of traffic monitoring systems. One notable approach is the use of GPS-based vehicle tracking systems, which utilize devices like Raspberry Pi and GPS antennas to monitor public vehicles. These systems continuously receive latitude and longitude values, allowing for real-time tracking of vehicles from their source to their destination. Similarly, Arduino-based real-time GPS trackers have been implemented to monitor salesmen, private drivers, and vehicle safety, providing a reliable method to observe and track expensive cars and their activities.

Another prevalent method involves Android app-based vehicle tracking systems that combine GPS and GSM technologies. In these systems, a GPS module receives the vehicle's location, which is stored in a microcontroller's buffer. When a registered mobile number sends a request, the location data is sent back via SMS, allowing for efficient

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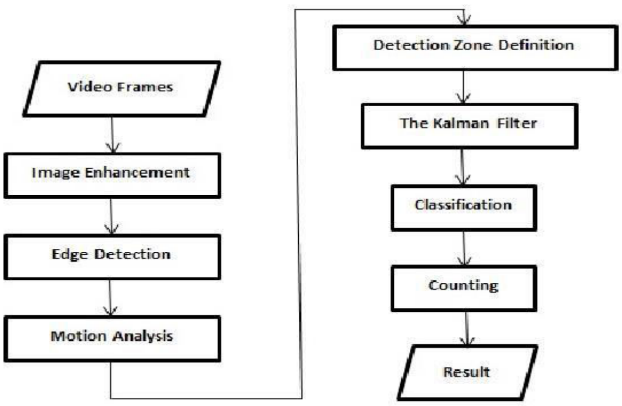
vehicle tracking. Additionally, systems integrating GPS, GSM, and GPRS services have been proposed to continuously update vehicle locations on a server, facilitating mobile-based monitoring and addressing organizational needs for vehicle tracking.

In the realm of intelligent transportation systems, accident detection, and vehicle tracking have also been explored. Researchers have developed systems that use vibration or piezoelectric sensors to detect traffic accidents, with GPS modules providing precise location data. This information is then sent to nearby ambulances via GSM modules, ensuring a quick response to emergencies. Furthermore, vehicle classification techniques have been refined through various methods, including artificial neural fuzzy inference systems, semantic segmentation of aerial images, and virtual detection zones. These approaches enhance traffic surveillance by accurately categorizing vehicle types, ultimately contributing to more effective traffic management and reduced accident rates.

In addition to GPS and GSM-based tracking, significant research has focused on enhancing vehicle detection and classification using advanced image processing and machine learning techniques. For instance, Murugan and Vijaykumar developed an automatic moving vehicle detection and classification system using an Artificial Neural Fuzzy Inference System, which improves the accuracy of traffic surveillance by effectively distinguishing between different vehicle types. Audebert et al. introduced a method for vehicle detection and classification through semantic segmentation of aerial images, providing high precision in identifying vehicles from overhead views. Seenouvong et al. proposed a vehicle detection and classification system based on virtual detection zones, demonstrating its efficacy in urban environments. Moreover, Dong et al. utilized a semi-supervised convolutional neural network for vehicle type classification, leveraging deep learning to achieve superior performance in diverse traffic conditions. These advanced methodologies underscore the potential of combining traditional tracking technologies with cutting-edge computer vision techniques to create robust and efficient vehicle detection and counting systems.

III. METHODOLOGY

The system under consideration seeks to identify, locate, and follow automobiles inside video frames to categorize them into three distinct sizes. The three primary elements of this system's architecture are vehicle categorization, foreground extraction, and background learning. extraction of the foreground, picture enhancement, and background removal[7].



Here is how the suggested method for counting and identifying vehicles is shown:

A. Grayscale Image Generation and Image Enhancement

The procedure should be carried out in the grayscale picture domain for better vehicle detection results. Consequently, every video frame is converted from RGB to grayscale. Every frame needs to be contrasted with the backdrop to reach the right threshold level and improve the outcomes in comparison to the input image[13]. In this paper, the power-law approach is applied among other grayscale conversions. As illustrated in Figure 2, experimental results under different conditions demonstrate that the optimal outcomes are achieved when the γ value is set to 1.2. The figure displays sections A, B, and D as grayscale versions with gamma values of 0.2, 2.2, and 1.2, respectively, with section A also shown as the original RGB colour frame input. This graphic represents the effects of applying various γ values to the grayscale-converted image.

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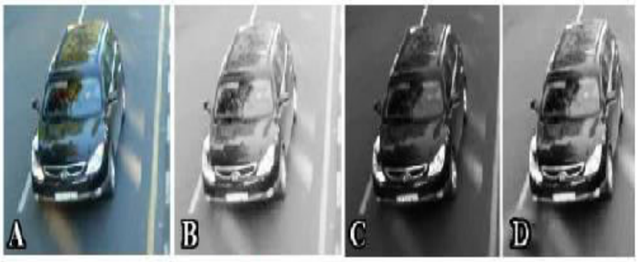

Figure 2. Input RGB video frame (A) and grayscale converted with different γ values (B, C and D)

B. **Edge Detection**

Edges, contours, and points are three important elements that are present in every picture (video frame) and are essential for accomplishing detection goals. Edge pixels are one of these elements that work well. By processing image pixels, we can identify edge pixels, which are crucial features of vehicles in a highway video frame. In this study, the Sobel operator, a widely used technique for edge detection, is employed. Figure 3 presents the results based on equation (2). The edge detection process produces a threshold or binary image that highlights the detected edge pixels.

Figure 3. A: Original image B: Edge detection result

C. **Detection Zone**

A portion of the screen known as the detection zone is the area where, when cars enter it, the boundaries of moving vehicles are shown as bounding boxes. This area, which occupies one-third of the screen's height and one-half of its width in the center, takes into account the smallest and largest observable car sizes in pixels. There is room for both little and large automobiles in this traffic-heavy location. Preventing perspective problems and inaccurate vehicle type counts is the main objective of creating this zone. The proposed method indicates that during the background subtraction process, a vehicle is detected across three consecutive frames. A bounding box is then drawn around the edges of the detected moving vehicle in the binary image.

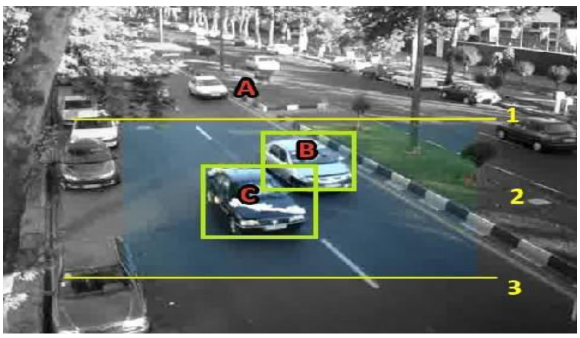

Figure 4: Detection Zone

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D. **Kalman Filter**

The Kalman filter is used in this system to refine location estimations derived from edge detection methods, therefore counting and classifying cars. Although edge detection is capable of detecting moving objects, noise and object movement frequently cause it to offer inaccurate locations. In order to minimize noise disruptions, the Kalman filter estimates each vehicle's present position as well as its future locations in an ideal manner. In addition to eliminating inaccurate counts from cars traveling in the wrong way, this filtering strategy makes sure that only vehicles traveling in the intended direction are recorded.

This research suggests using Canny edge detection algorithms and Kalman filters to improve vehicle recognition and counting systems in response to the difficulties presented by contemporary urban traffic. These approaches offer reliable means of locating and monitoring cars in a variety of scenarios, which helps to tackle important problems like more cars per capita, a wide range of car kinds, bad weather, low light and nighttime conditions, edge computing constraints, cybersecurity risks, difficulties with scalability and integration, and privacy issues. In real-world applications, the system may achieve improved accuracy and dependability by incorporating these cutting-edge image-processing approaches

E. **Vehicle Counting and Classification**

The system has features for categorizing and counting cars, which are essential for infrastructure development and traffic control. Bicycles and motorbikes, motorcars, pickups and minibuses, and buses, trucks, and trailers are the four main categories of vehicles[8]. Based on the measurements of the bounding boxes that were found in the video frames, this categorization was made. The bounding boxes visually depict each type of vehicle by using a different colour, making identification and analysis easier.

The method uses distinct counters for every kind of vehicle in addition to a total counter for all cars for counting purposes. By omitting cars that stop, turn, or move inappropriately, these counters ensure accuracy by only increasing when vehicles travel in the designated direction. With the help of this method, efficient traffic management and monitoring are supported by a trustworthy vehicle count and categorization.

Figure 5. Vehicle classification-coloured bounding boxes

To classify passing vehicles into the specified categories, the width and length of each vehicle's bounding box must be measured in pixels. The vehicle type allocation is based on the area of each bounding box. For simple visual identification, each kind of vehicle is represented by a distinct colour for the rectangle.'

In this study,

•Type 1 (motorcycles and bicycles) is represented by red rectangles, as shown in Figure [5].

•The Type 2 (motorcars) rectangles are shown in green.

•Blue rectangles stand for Type 3 vehicles, which include pickups and minibuses.

• Yellow rectangles stand in for Type 4 vehicles, which include trucks, buses, and trailers.

F. **Counting similar vehicle types**

Important data acquired with this vehicle detection method is shown in Figure 7. The total number of passing cars, highlighted in yellow, assists in traffic flow analysis over a period [7]. The appropriate counters have identified and tallied the various types of vehicles by calculating the height and width of their bounding boxes in pixels.

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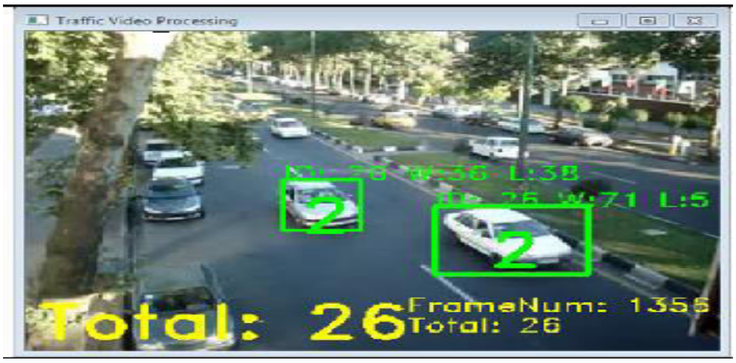

Figure 6. Counting similar vehicle types

Some notable aspects presented in Figure 7 include:
•The directions of the two cars that were identified are identical.
•Although the white automobile in the back has not been counted, both cars are within the detection zone. Both of the tallied vehicles have green rectangles around their borders, designating them as Type 2 vehicles. This categorization is supported by the green numbers inside the enclosing boxes[15].

The system's capacity to precisely identify, categorize, and count cars is supported by this thorough analysis, which improves traffic management and monitoring initiatives.

IV. EXPERIMENTAL RESULTS

The method was tested in a real-condition test using an AVI format video with a frame rate of 29 frames per second and 124 passing vehicles. The technique was implemented using C++ and the OpenCV 2.4.8 library[11]. The experiment involved tests to measure the accuracy of vehicle counting and classification, ensuring the effectiveness of the proposed method.

Detection Test:

The detection test evaluated the method's accuracy in counting the number of vehicles. The results are shown in Table 1.

Real Number of Passed Vehicles	Counted Number of Vehicles by the Method	Number of Errors
124	119	5 (4%)

Table 1

The detection test revealed that 3 out of 5 errors occurred when two moving vehicles of similar colours and sizes were in proximity, causing the method to fail in distinguishing between them. This limitation could be addressed by using advanced techniques or integrating features like vehicle shape or speed. Another issue was the method's failure to exclude non-vehicle moving objects, such as pedestrians or animals crossing the road. To address this, incorporating factors like motion speed and direction into the detection algorithm is essential. This will help differentiate vehicles from humans or animals.

Classification Test:
The second test evaluated the accuracy of the vehicle classification component. For this experiment, 119 vehicles identified in the detection test were included [3]. A confusion matrix summarizing the results and visualizing the performance is shown in Table 2.

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	Bicycles	Motor Cars	Mini Buses	Trucks
Bicycles	13	1	0	0
Motor Cars	1	71	3	0
Mini Buses	0	1	18	1
Trucks	0	0	1	8

Table 2

The method's classification accuracy is around 95%, with a small number of misclassifications. Misclassifications were found in bicycles, motorcycles, motor cars, pickups, mini buses, and buses. To improve accuracy, solutions include selecting an appropriate detection zone for long vehicles, using pattern recognition methods to differentiate between vehicle types, combining vehicle shape information with occupancy pixels, and defining isolated detection areas for each lane. Despite some challenges, the observed errors are considered acceptable as they do not significantly impact the overall estimation of traffic flow intensity [9]. The method's accuracy, even with minor errors, remains adequate for traffic control and analysis. While improvements are continually sought, the current performance supports its intended applications in traffic management and analysis.

V. CONCLUSION

This paper presents a vehicle detection and counting system using digital image processing techniques. The system, which uses the Kalman filter algorithm and image processing methods, accurately counts passing vehicles and classifies them by type. It has low detection and classification errors of around 4% and 5%, respectively. The study emphasizes the practicality and efficiency of using image processing algorithms like the Canny Edge Detection Algorithm for vehicle detection. Unlike traditional methods that rely on expensive sensors, this software-based approach offers faster processing speeds and simplified implementation using MATLAB and Python with OpenCV. Challenges like occlusion and camera angle variability affect detection accuracy, suggesting future improvements through enhanced feature classification and camera calibration techniques. The method is adaptable for existing video footage and potential integration into live streaming applications with microcontrollers.

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