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Vehicle Detection and Counting System based on Video

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Abstract: This paper presents an efficient vehicle detection and counting system using OpenCV and Python. The system leverages computer vision techniques for vehicle detection, tracking, and classification. By implementing background subtraction, image filtering, and segmentation methods, the system accurately identifies and counts moving vehicles from video sequences. The proposed approach is cost-effective, portable, and suitable for various applications such as highway monitoring, traffic planning, and toll collection. Experimental results demonstrate the system's effectiveness in detecting and counting vehicles in real-world scenarios, showcasing its potential for enhancing traffic management and analysis processes. Additionally, the paper explores alternative classification methods, including Contour Comparison (CC) and Bag of Features (BoF) with Support Vector Machine (SVM), contributing to the advancement of vision-based vehicle detection and classification systems.

Keywords: OpenCV, computer vision, traffic surveillance, vehicle detection, real-time monitoring, traffic management, road safety.

I. INTRODUCTION

In recent decades, the global landscape has witnessed an unprecedented surge in urbanization and population growth, accompanied by a corresponding increase in vehicular traffic. This rapid urban expansion has posed significant challenges to traditional traffic management methodologies, which struggle to keep pace with the evolving demands of modern transportation systems. Congested roadways, extended commute times, and escalating concerns regarding road safety have become emblematic of the burgeoning urban centers worldwide [2].

The pressing need for efficient traffic management solutions has catalyzed the exploration of innovative approaches to address the multifaceted challenges posed by urban mobility. Traditional techniques, though effective to a certain extent, confront inherent limitations in scalability, adaptability, and cost-effectiveness. The advent of smart cities and the proliferation of the Internet of Things (IoT) have emerged as transformative forces, offering novel avenues for redefining the landscape of traffic management [1].

Within this paradigm, the integration of computer vision with IoT infrastructure represents a paradigm shift in traffic surveillance and control systems. By harnessing the power of real-time data collection, analysis, and decision-making, these integrated systems promise to usher in a new era of responsive and adaptive traffic management solutions. The synergy between computer vision and IoT technologies empowers traffic authorities with actionable insights into traffic dynamics, congestion patterns, and potential safety hazards, thereby enabling more informed decision-making and proactive intervention strategies [1].

A pivotal application of computer vision in this context lies in the realm of vehicle detection and recognition. The ability to discern and classify various types of vehicles, ranging from cars and trucks to bicycles and pedestrians, holds profound implications for traffic surveillance systems. Beyond mere vehicle tracking, computer vision-enabled systems can discern aberrant behaviors such as reckless driving, illegal parking, or traffic accidents, facilitating expedited responses and mitigating potential risks [5].

Central to the efficacy of these systems is the integration of machine learning algorithms, which enable continuous refinement and enhancement of detection accuracy and reliability over time.

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By leveraging vast repositories of labeled data, machine learning models can iteratively learn and adapt to evolving traffic dynamics, thereby maximizing the utility and effectiveness of traffic surveillance systems [7].

Moreover, the convergence of vehicle detection systems with other smart city initiatives, such as intelligent transportation systems (ITS) and connected vehicle technology, promises to unlock unprecedented synergies in enhancing overall traffic efficiency and safety. Real-time data streams from vehicle detection cameras can be seamlessly integrated into broader transportation management frameworks, enabling dynamic adjustments to traffic signal timings, proactive rerouting of vehicles away from congested areas, and timely dissemination of safety advisories to motorists [3].

In conclusion, computer vision-based traffic surveillance systems, underpinned by cutting-edge technologies like OpenCV, represent a paradigmatic shift in the realm of modern traffic management. By leveraging the capabilities of real-time data analysis and machine learning, these systems hold the potential to revolutionize how we monitor, analyze, and optimize traffic flow in urban environments. With their scalability, cost-effectiveness, and adaptability, computer vision-enabled traffic surveillance systems offer a compelling solution to the myriad challenges confronting contemporary transportation networks, ultimately paving the way towards safer, more efficient, and sustainable urban mobility ecosystems [5].

II. RELATED WORK

Related work in the field of vehicle counting and detection using OpenCV involves various methodologies and techniques employed by researchers to address the challenges posed by real-world traffic surveillance scenarios. 'Tursun and Amrulla' proposed a real-time vehicle counting system utilizing an optimized virtual loop method, which tracks vehicle movements within a defined tracking zone to accurately count passing vehicles. Lei et al. introduced another video-based vehicle counting system employing adaptive background estimation and Gaussian shadow elimination to enhance accuracy, particularly in scenarios with varying visual angles and lighting conditions.

'Bas et al' developed a video analysis method incorporating adaptive bounding box-sizing for vehicle detection and tracking, with a focus on estimating vehicle distances from the camera and defining regions of interest within the image. Meanwhile, Mithun et al. proposed a vehicle detection and classification system utilizing time-spatial images and multiple virtual detection lines, integrating a two-step K nearest neighborhood algorithm for improved accuracy across different lighting conditions.

Additionally, 'Habibu Rabiu' introduced a vehicle detection and classification system specifically tailored for cluttered urban intersections, employing background subtraction and Kalman filter algorithms for vehicle tracking, alongside Linear Discriminant Analysis for classification. These approaches highlight the importance of accurate foreground detection in video-based traffic surveillance systems, with techniques such as frame differencing, optical flow field methods, and Gaussian Mixture Models being commonly employed.

Furthermore, researchers like 'Suryatali and Dharmadhikari' proposed a computer vision-based vehicle detection and classification system using Kalman filtering for background subtraction, followed by OpenCV library integration for object detection. 'Nilakorn et al'. presented a vehicle detection and counting prototype employing various steps for background subtraction and object enhancement, leveraging techniques such as thresholding and morphological dilation. These efforts demonstrate ongoing advancements in the development of robust vehicle counting and detection systems capable of handling complex real-world scenarios, although challenges remain in addressing issues such as adverse weather conditions and occlusions.

III. METHODOLOGY

The system could be used for detection, recognition and tracking of the vehicles in the video frames and then classify the detected vehicles according to their size in three different classes.

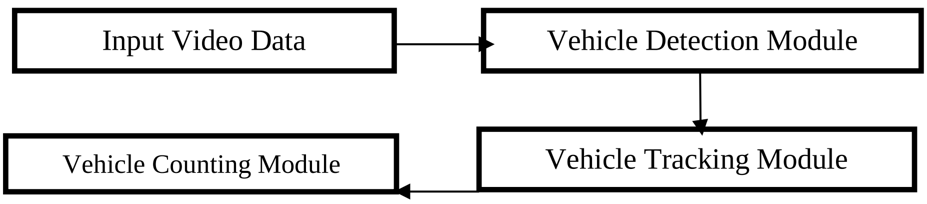

Fig.3.1. Block diagram of proposed vehicle detection and counting system.

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The proposed system is based on three modules which are background learning, foreground extraction and vehicle classification as shown in fig. 3.1. Background subtraction is a classical approach to obtain the foreground image or in other words to detect the moving objects.

A. Background Learning Module:

This is the first module in the system whose main purpose is to learn about the background in a sense that how it is different from the foreground. Furthermore as proposed system works on a video feed, this module extracts the frames from it and learns about the background. In a traffic scene captured with a static camera installed on the road side, the moving objects can be considered as the foreground and static objects as the background. Image processing algorithms are used to learn about the background using the above mentioned technique [1].

B. Foreground Extraction Module:

This module consists of three steps, background subtraction, image enhancement and foreground extraction. Background is subtracted so that foreground objects are visible. This is done usually by static pixels of static objects to binary 0. After background subtraction image enhancement techniques such as noise filtering, dilation and erosion are used to get proper contours of the foreground objects. The final result obtained from this module is the foreground [3].

C. Vehicle Classification Module:

The third and the last module in the proposed system is classification. After applying foreground extraction module, proper contours are acquired. Features of these contours such as centroid, aspect ratio, area, size and solidity are extracted and are used for the classification of the vehicles [1].

The first step of the proposed system is to grab a data video on which we want to perform the classification. After video selection, ROI is defined. ROI needs a careful human supervision because region of interest and imaginary line plays important role in classification. After ROI is defined, the system performs series of tasks i.e. applying background mask, subtracting mask, performing binary threshold, morphology using erosion and dilation, median blur, applying masked data to the frame, convert frame to gray scale. Contours are detected after these operations [6]. Once contours are detected; system analyses the moments of the contours, marks the detected contours and centroid is calculated. If calculated centroid is in the range of the diagonal, system moves towards further operation for classification else system will be redirected towards the detection of contours again. The last step is the classification; the system classifies the vehicles with two different methods i.e. using SVM and with the CC.

The classification using SVM is used in which SIFT features are calculated for the contours and used as input to the SVM. Three types of vehicles are identified by SVM which are Low Transport Vehicle (LTV), Medium Transport Vehicle (MTV) and Heavy Transport Vehicle (HTV). SVM classifies the vehicle using the features extracted with the help of SIFT and then corresponding variables are incremented according to the output i.e. LTV, MTV and HTV. In addition, classification of the vehicles using CC is done. Once the centroid calculated is in the range of diagonal; the properties of contours are extracted. The features extracted are compared with the assumed values and output is calculated. In the end the corresponding variables are incremented according to the output[5].

A. Region of interest:

ROI is a particular portion of an image on which an operation is to be performed. ROI gives the flexibility to just work with in a particular region instead of manipulating the whole image. In proposed system, selection of region of interest is very important to reduce the false positives in the detection and classification of vehicles. Selection of ROI is pretty simple, once the video is started, the user has to press the “I” key on the keyboard to activate the input mode. Afterwards the user uses his mouse to select the four points on the video which defines the region of interest. Once selected, pressing of any key on the keyboard selects the region of interest, crops it and shows the new video feed on only that region [2].

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Fig.3.2. Region of interest selection input mode.

Fig. 3.2 shows ROI selection input mode. Notice the four green dots on the screen, these are the points defining the ROI and were placed using mouse clicks.

B. Background subtraction:

Proper background subtraction is a vital pre-processing step in creation of any visual surveillance system as the accuracy of whole process of classification of the objects depends on it. The systems like visitor counter [2] in which a static camera captures the video of people entering a building and the system could count the number or a system where a camera captures the video of the vehicles on the road for the similar purpose.

The background subtraction could be an easy job if we already have an image of the background like the image of the building or the road. In cases defined above, background image could be removed and foreground objects could be obtained but most of the time the situation is varying. The backgrounds can be dynamic or initial information of the scene might not be available. Furthermore, the background subtraction becomes more difficult if the objects in the video also have shadows since they also move with the people or vehicles, then the normal background subtraction will detect the shadows as foreground objects too.

Several algorithms have been introduced for the situations like that; some of them are implemented in openCV such as Background Subtraction MOG [3] which use Gaussian distributions to create the model of the background in the image. It uses about 3 to 5 Gaussian distributions for this purpose. Another background subtraction implemented in openCV is called Background Subtractor GMG which is based on [2] and combines the background image estimation technique with Bayesian segmentation.

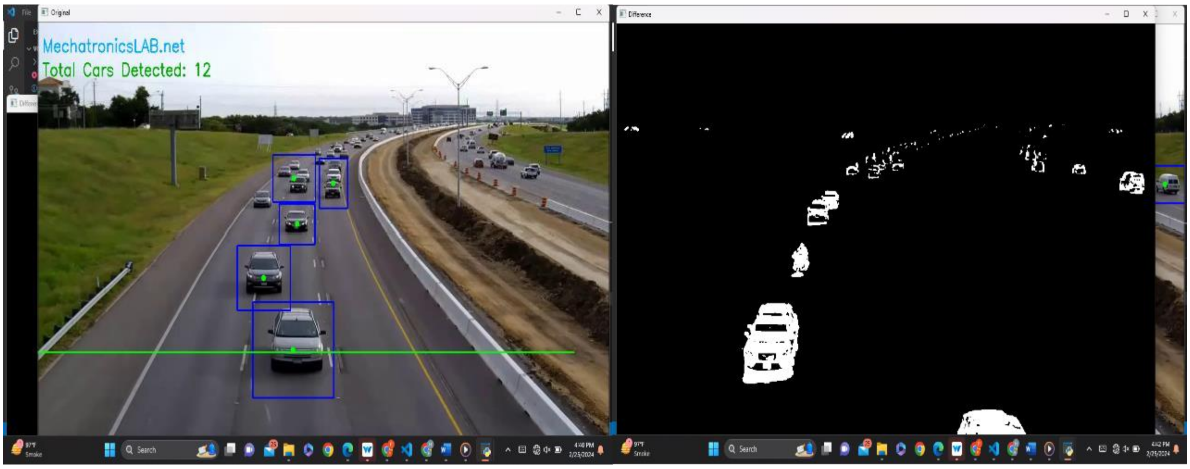

Fig.3.3. Frame of video before and after subtraction of background Figure 3.3 firstly scans the video and display both the video and only cars at a time.

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The algorithm used in the implementation of proposed system is called backgroundSubtractorMOG2. It is based on two studies [1] and [2] by 'Zikovic'. One of the important features of this algorithm is that unlike [6] in which the number of distributions for the creation of background model are defined, BackgroundSubtractorMOG2 uses an automated approach and selects an appropriate number of Gaussian mixtures for the pixel. Furthermore algorithm is also better at handling the illumination changes in the scene. The algorithm also gives the ability to define if the shadow of the objects is to be detected or not. Note that the default settings of the implementation are set to detect the shadows.

C. Contour extraction Contours are the boundaries of the shape which are used for the shape detection and recognition. The accuracy of the process of finding the contours can be defined as the canny edge detection performed on a binary image. OpenCV provide cv2.findContours() method to find the contours.

D. Counting vehicles Vehicle counting can be done by checking if the centroid of a vehicle has touched or crossed the imaginary line in ROI. Imaginary line is the line that diagonally appears by connecting two ROI points. Once the centroid of a vehicle in ROI crosses the imaginary line, the system counts the vehicle. From fig. 4, it is noticeable that when centroid of vehicle touches the imaginary line in ROI, it increments in the variable "Total" and variable of respective category.

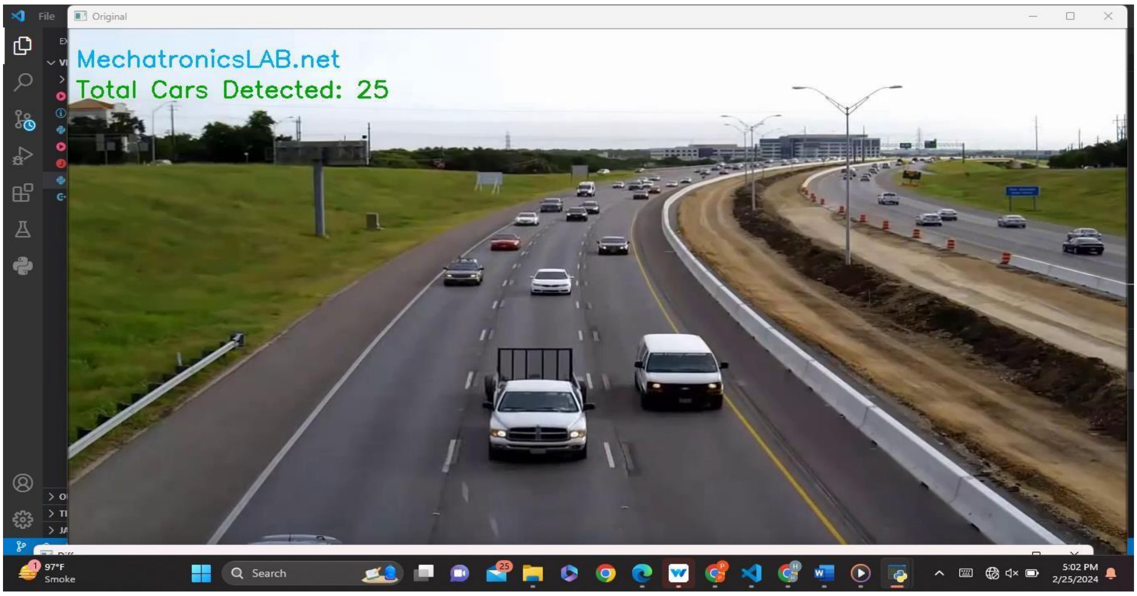

Fig.3.4. Scans the video and detect the vehicle's and counts the no of vehicle's in the video.

IV. CONCLUSION

The implementation of vehicle detection and counting using OpenCV presents a viable solution for monitoring traffic on expressways and highways. By leveraging computer vision techniques, the system effectively detects moving vehicles, counts them, and can potentially classify them using machine learning algorithms. The approach demonstrates robustness, particularly with the use of the Connected Components (CC) method, which outperforms other techniques such as Bag of Features (BoF) and Support Vector Machine (SVM) in terms of accuracy and classification closeness to ground truth values. However, several limitations and areas for improvement are identified. Firstly, the system struggles with detecting occluded vehicles, which affects both counting accuracy and classification. Introducing second-level feature classification, such as color-based classification, could mitigate this issue. Additionally, the system requires human supervision to define the region of interest and relies on judgment for accuracy, suggesting a need for automation in this aspect. Camera angle calibration techniques could enhance the system's efficiency by providing better views of the road. Moreover, the system currently operates effectively during daylight but faces challenges in detecting vehicles at night due to reliance on visible foreground objects. Utilizing more sophisticated image segmentation techniques and incorporating advanced artificial intelligence operations could address this limitation and improve accuracy.

In conclusion, while the implemented vehicle detection and counting system using OpenCV offers a promising solution for monitoring traffic on expressways and highways, there is ample room for enhancement. Addressing the identified limitations and incorporating advanced techniques could lead to a more robust and reliable system capable of meeting the growing demands of traffic management in various scenarios.

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