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ANALYSIS ON APPLICATIONS OF MACHINE LEARNING BASED IMAGE PROCESSING FOR VEHICLE DETECTION AND COUNTING SYSTEM

K.Prasanthi [1] , S.Vishnupriya Chowdhary [2] ,T.Lakshmi Prasanthi [3],Dr.N. Neelima [4],

Department of Electronics and Communication Engineering,

Amrita School Of Engineering, Bengaluru,

Amrita vishwa vidyapeetham, India.

ABSTRACT

In this study, we investigate a traffic surveillance system's vehicle detecting method. For the purpose of detecting vehicles, this system incorporates CCTV cameras. Detection of a vehicle is always the first step. For the detection of a car in the footage, Haar Cascades are employed. This work presents a brand-new high-definition highway vehicle dataset with 57,290 annotated instances spread across 11,129 photos. Vehicle detection using deep learning requires a complete dataset, and the suggested dataset has tagged microscopic items in the image to give that data foundation. To begin, a newly proposed segmentation method is used to extract the highway road surface from the image and divide it into two sections: a remote region and a nearby region. This step is critical to the proposed vehicle recognition and counting system. In order to identify the type and position of the vehicle, the YOLOv3 network incorporates the following two areas: ORB method is used to obtain vehicle trajectories, which can be used to determine the vehicle's driving direction and the total number of cars. The proposed methods are tested using a variety of highway surveillance films from different scenes. According to the results of the experiments, the proposed segmentation method improves detection accuracy, particularly for small vehicle objects.

1. INTRODUCTION

In this paper, we'll look at the most accurate methods for identifying and monitoring a single vehicle in a given area of interest. Vehicle identification and counting are critical components of many traffic management systems in urban areas. Car detection and counting are the primary goals, and the ability to do so on roadways, highways, and in narrow lanes is essential. Foreground features, such as haar cascades, are used in our system, which receives video or picture data and analyses it to deliver an exact count of vehicles spotted.

In urban areas, traffic monitoring has become increasingly important due to rapid advancements in intelligent video analysis. If you utilise classic sensors, such as magnetic detection devices and loop detection devices [1–4], you risk damaging the road surface. The expense of this task is also considerable because many of these sensors have to be deployed in metropolitan areas. These include surveillance cameras, which can offer a video stream for vehicle detection and counting, as well as other sensors. Occlusion, shadows, and a limited vision are among issues that must be overcome when employing surveillance video cameras. Lin used occlusion detection and queue detection to tackle the occlusion issue and address the ensuing issues. Wang was able to identify shadows based on the properties of shadows, such as lesser luminance and the absence of textures. Occlusion was avoided through Douret's employment of multiple cameras to cover a vast region. When Using binocular stereo matching on the corrected images, two omnidirectional cameras mounted on the vehicle can create a dynamic panoramic surround map of the area surrounding the vehicle. Counting the number of vehicles on the road can also be done using vehicle detection and tracking. Srijongkon proposed an ARM/FPGA processor-based vehicle counting system that uses adaptive background subtraction and shadow elimination in order to count vehicles on the video display. A motion estimation-based vehicle counting system was created by Prommool (block matching and optical flow combination). Area boxes are used to decide whether or not a vehicle is allowed to pass through an intersection. Based on a colour space model, Swamy demonstrated a vehicle recognition and counting system employing a pre-defined line to count vehicles based on colour and brightness distortion. In surveillance video sequences, Seenouvong [15] employs a background subtraction method to identify foreground cars, and then determines the virtual detection zone's centroid.

2. RELATED WORK ON VEHICLE DETECTION

Traditional machine vision algorithms and more complex deep learning methods are currently being used to detect moving objects with vision-based technologies. To distinguish between a moving object and a static background image, traditional approaches to machine vision use motion detection. In the field of background subtraction, there are a variety of techniques to choose from, including the methods described in [1], [3], and [4]. The pixel variance is calculated using the pixel values from two or three consecutive video frames. A threshold separates the shifting foreground from the rest of the image [3].

It is possible to identify the vehicle's stop by applying this strategy and reducing noise [5]. Video backgrounds can be created using information gleaned from a video's pre-existing video content [5]. Once the backdrop model is compared to each frame image, the moving object can be segmented as well. The video's motion region can be detected using the optical flow approach. Each pixel's velocity and direction of motion are represented by the created optical flow field [4]. SIFT and SURF approaches, which exploit vehicle features, have been widely adopted. 3D models, for example, have been used to detect and classify vehicles [6]. Using 3D ridges on the vehicle's exterior, it is possible to classify automobiles into three groups: cars, SUVs, and minibuses.

The use of overhead video to monitor traffic has increased in recent years. An programme created by Ruimin Ke uses interest points from two frames to derive vehicle speed information, and then applies the optical flow algorithm to track those points as they move over an aerial video. KLT features tracker was used to create an airborne video-registration method that can automatically estimate traffic flow parameters. A particle filter and KLT features were included in Cao's [18] framework for tracking UAV-based vehicles. Moving objects can be detected using an optical flow interest point extraction tool. Interest points are a time-saving method for efficiently extracting a feature from an interest region. As a result, noise is introduced into the subsequent tracker because of the intricacy of the scene in aerial recordings, which can be recovered as "interest points."

Image registration in real time from an unmanned aerial vehicle (UAV) has been proposed by Pouzet, who focuses on the detection of small moving objects. Both methods use image-registration to segment moving vehicles from aerial recordings by translating the previous frame to the current frame. Photos can be compared to one another and the scene studied using a reference coordinate system when they are registered. To track moving objects, Freis developed an algorithm that relies on background subtraction from images captured by an unmanned aerial vehicle (UAV).

An approach to vehicle detection using a UAV-based SIFT and implicit shape model was proposed by Chen (ISM). Guvenc had the idea for a piece on drone-based object recognition and tracking (UAVs). Classifies objects in wide-area motion footage using a cascade of support vector machine classifiers. This system is the work of Shi. Both appearance and movement are taken into account by LaLonde's cluster network for the detection of small objects in wide-area motion imaging. Even though wide-area motion footage recorded at extremely high altitudes is difficult to obtain with a universal UAV, research is focused on the detection of small objects. A vehicle counting approach from a UAV has been proposed by Wang employing a block sparse RPCA algorithm and low rank representation for vehicle counting. When in hovering mode, the drone records only static background shots. Multiple object tracking and management modules must be installed in order to accurately count the number of vehicles on the roadways.

3. METHODOLOGY

An overview of the system's major components is provided in the following paragraphs. The traffic scene video data must first be entered. The road's surface area is then surveyed and divided into sections. The YOLOv3 object detection method is used to identify vehicles in highway traffic. Vehicle box ORB features are extracted to complete the tracking of several objects.

With the road surface segmentation method depicted in Figure 1, highway area can be extracted. Both a far-off and a closer section of the road are visible from the camera. A vehicle detection method known as YOLOv3 is then employed to find the vehicles on the two roads. Because of the abrupt change in object scale, it is difficult to detect small objects. Our approach may be able to help alleviate this issue. The ORB algorithm is then used to track multiple objects. Using the ORB algorithm, two video frames depicting the same object are correlated by matching the box's features. This is where the math comes in. An object tracking trajectory is formed by analysing traffic data, including the number of vehicles in each category. This system improves object detection accuracy and creates an object tracking and traffic information gathering strategy from a highway surveillance video perspective.

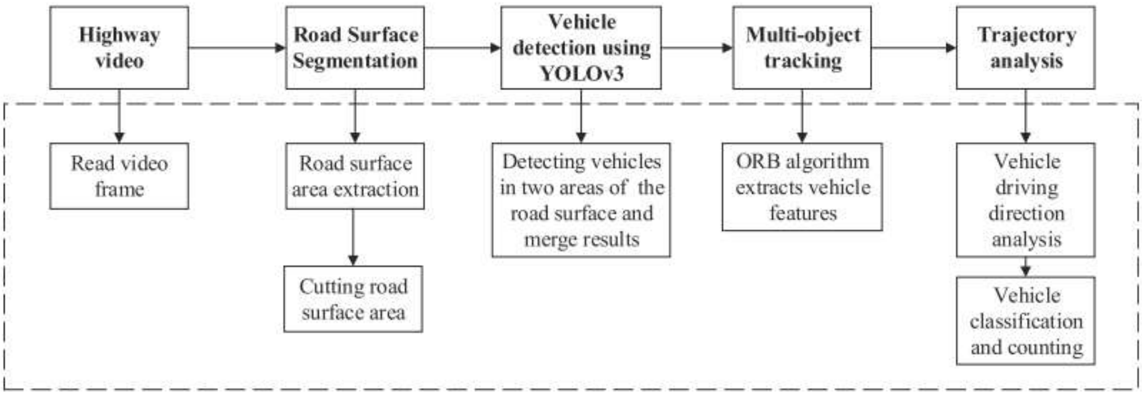


Fig. 1 Overall flow of the method.

Segmentation of the road's surface The extraction and segmentation of highway road surfaces is described in detail in this section. With the help of image processing techniques like Gaussian mixture modelling, we were able to improve vehicle detection results when using the deep learning object detection method. The area of view on the highway surveillance film is quite expansive. As a result, this study focuses on highway road surface area rather than automobiles themselves. At the same time, a specific portion of the image is dominated by the road's surface due to the camera's shooting angle. We were able to extract the video's highway road surface regions using this feature. Figure 2 depicts the road surface extraction procedure.

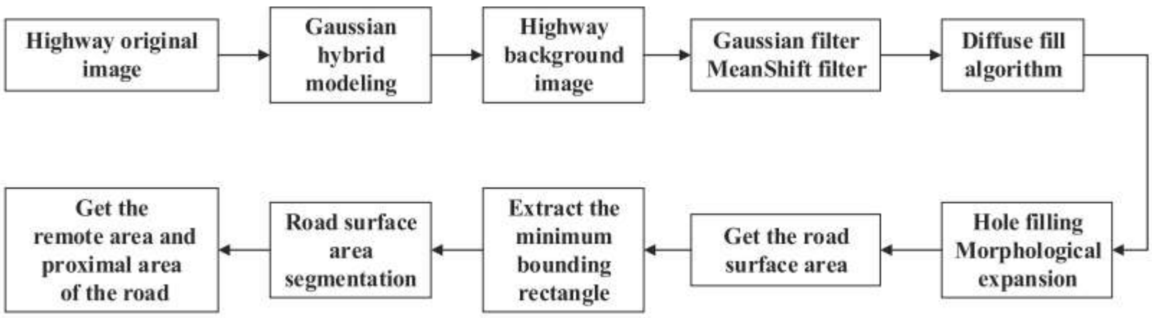
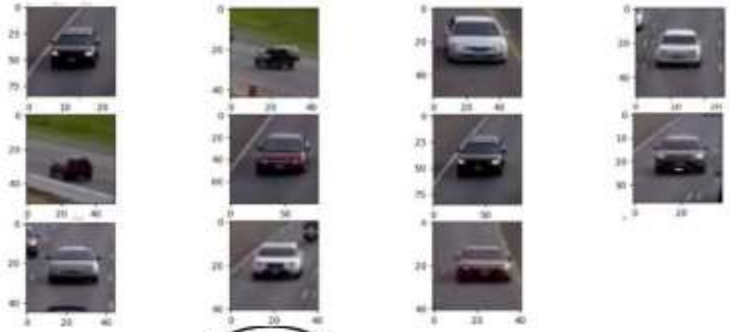


Fig. 2 Overall flow of road surface extraction .

3.1 Object Tracking

We were able to improve vehicle detection results by implementing surface extraction and division utilizing picture handling approaches, for example, Gaussian combination displaying when utilizing profound learning object discovery. An object's previously tracked location would be used if the new location was included in the previously tracked locations. Continuous identification of the observed vehicle in a video sequence is the foundation of vehicle tracking. Detection is made by drawing a line around the vehicle. The flowchart in Figure 3 depicts the whole procedure for tracking an object.



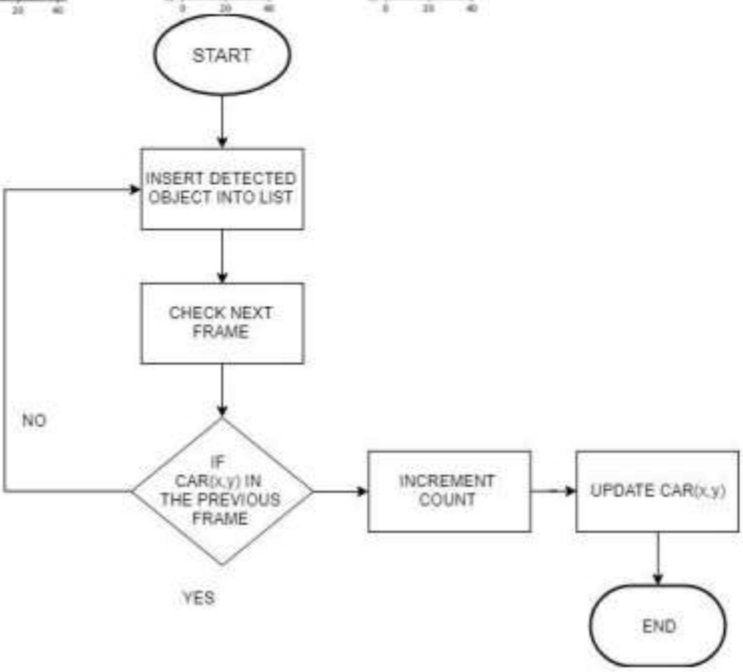


Fig.3. Flowchart of Object Counting.

AdaBoost's powerful classifier is capable of detecting objects level by level on a cascading hierarchy. Up until the subwindow predicted an automobile, the next level of filtering relied on a positive object in each subwindow as a feed for the next level of filtering. Sub-windows that didn't contain positive objects were marked as background and separated from sub-windows that did

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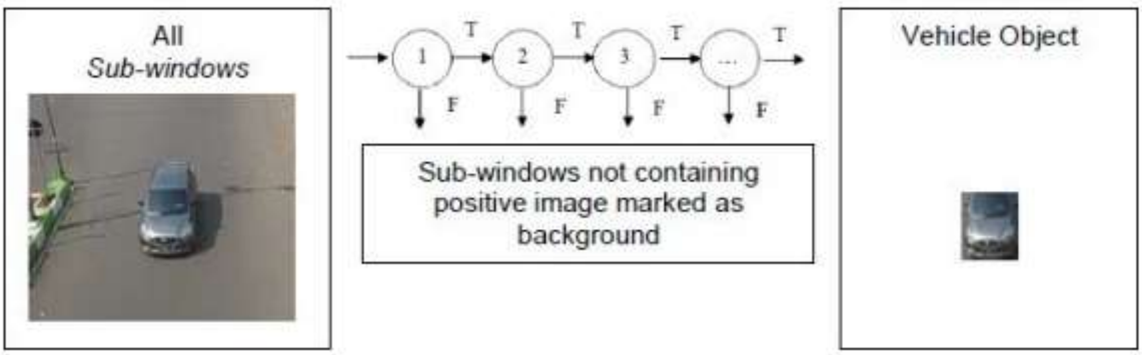

Fig. 4. Cascade Object Detection Scheme.

4. RESULTS AND ANALYSIS

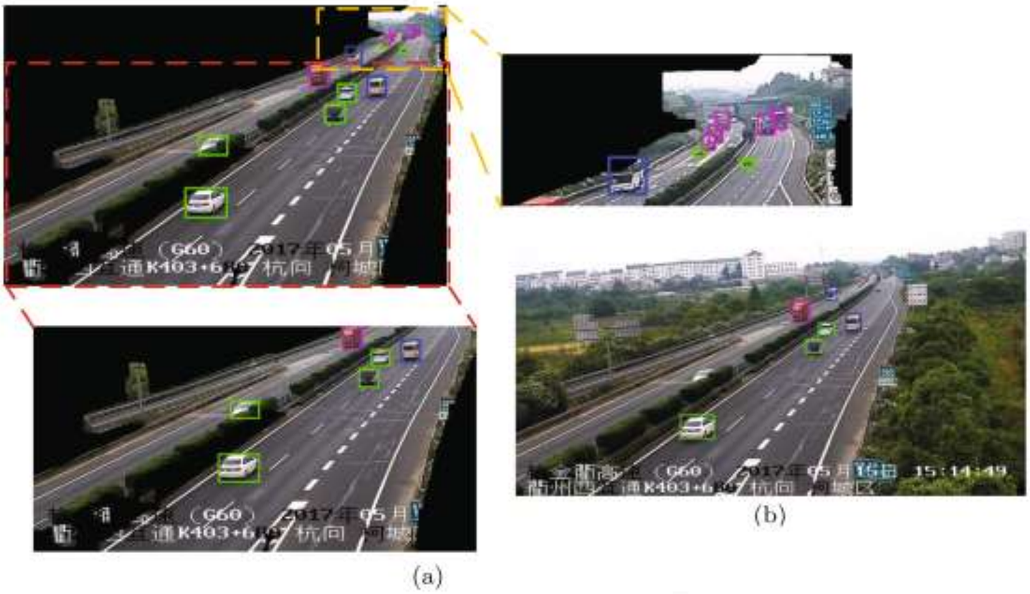

Fig. 5 Results of object detection in a single video frame. Car, bus, and truck regions are denoted by the color-coded boxes in a fuchsia, green, and blue scheme. a Our method; b the full-image detection method.

Vehicle detection in a variety of highway situations was carried out using our trained model, which analysed 3000 frames of photos. In order to detect vehicles, we removed the road surface and separated it into sections. When we tested our method against one that detected images with a resolution of 1920*1080 into the network (without partitioning the road surface), the results are displayed in Figure 5.

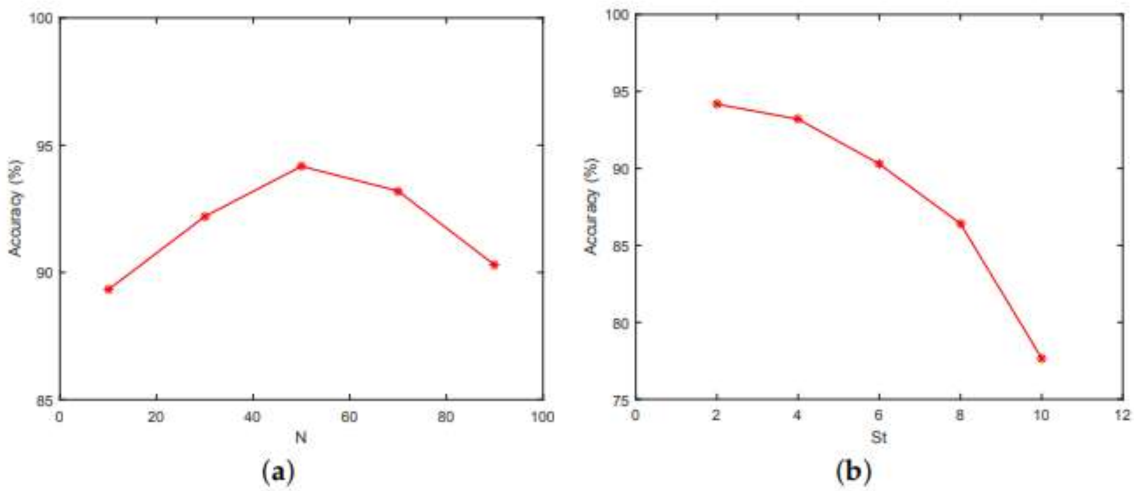

Figure 6. With different parameters, how accurate is vehicle counting? (static background). Static video was used to test our method, with various boundaries: (a) the impact of N on precision when the worth of St is fixed to 2; and (b) the impact of St on exactness when the worth of N is fixed to 50.

Detection outcomes are clearly influenced by detector parameters. In addition, on TEST VIDEO 1, we ran several tests to see how accurate the car counting was. Varied parameter values have different effects on accuracy, as seen in Figure 6. Figure 6 shows that the maximum level of precision is reached when N is set to 50 and St is set to 2.

(a) (b)

Figure 7. Post-processing examples (static background). Images are post-processed using the median filter. This segmented image had noise in it, so we chose an area to filter to reduce that noise: (a) the original image; and (b) the final result of detector.

It is therefore critical to use accurate parameter values. Figure 7 depicts the more full segment outcomes following the morphological processing.

CONCLUSIONS

Utilization of an article discovery and following calculation for observation video successions has brought about a superior quality vehicle object dataset. In order to maximise ROI, the highway's road surface area had to be reduced. The YOLOv3 object detection algorithm and the annotated highway vehicle object dataset were used to discover the model for highway vehicle end-to-end detection. Static and shifting backgrounds can be accommodated by our solution. A foreground detector is used to compensate for tiny changes in the real scene when the background is static. The camera's motion is estimated using an image-registration technique, allowing for the detection of a moving vehicle. On top of all that, our framework incorporates an online-learning tracking mechanism that allows us to keep up with changing vehicle shapes and scales in images.

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