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Image-Based Vehicle Detection using Various Features

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Abstract:- There are frequent vehicle accidents in our country due to reckless driving and also break the driving rules. So, main purpose for this research comes from the situation of our country worsts vehicles. Now-a-days in our country vehicles damage are increasing rapidly. This is why a concept that emphasizes on the betterment of our country traffic environment. Here, apply two methods for detect the vehicle. Such as Lens-based vehicle Classifier and Haar cascade classifier. Lens-based Vehicle Classifier and Haar cascade classifier used for utilize the object detect of the vehicle. And all the procedure is held with camera and sensor to detect the vehicles. In the primary level, DSLR camera takes multiple photographs in a different way after the image is resister in database. All the process is held like heat map, bounding box, threshold and merged box in database. So, heat map highlights the image and send to the bounding box for predict. This prediction is also a smaller number of images. Heat map are used for bounding box that threshold of 85% probability of any class of object. Regressor when included the output of image pixel are merged. And finally, all the procedure done and get a result of vehicle detection that accuracy 85% or less.

Keywords:- *Computer Vision & Digital Image* ***Processing.***

I. INTRODUCTION

It is a challenging task to detect vehicle damage automatically when an accident occurred. After an accident, it's very difficult to use photographs taken at the accident scene. This fascinating repertoire of computer vision problems solving is also a challenging task.[7] Vehicle has a very metallic body and photographs taken to the uncontrolled area or environment, is also challenging applying computer vision techniques. Here, using different methods such as image segment is one of the major problems in computer vision. Image segment techniques photograph pixel defends on different color and texture. Therefore, it's a challenging task for this object to segment sub parts and boundary cues (both parts of the vehicle).[18][20] The original parts and projected parts of the 2D model are not matched in the photograph damage vehicle. Image segment method using for contour initial information for this 2D pose of projecting parts model. Hence, we mainly focused on the vehicle's image and also reflected the surface of the vehicle body.[9][15] Now, another problem is estimation in computer vision that application is used in vision image analysis. Generally, the process of estimation of obtained an object part of location to its surroundings. Here, our work is also restricted for non-articulated objects. 2D pose estimation required application to application by accuracy and nature.[33] Here application depends on subset 2D pose parameters and fines the result of damage to the vehicle. In the research paper overall objective is to be able to automatically detect mild damage in vehicles using photographs. And these photographs taken by the camera or mobile phone.[11][19].

II. DETECTION CONCEPT AND METHOD

A. LVC Method

In this method, at first take some photographs of the vehicle (car, bus and bike) by DSLR camera. DSLR cameras capture the photographs by three types of lens like Kit lens, zoom lens and Prime lens. Kit lens (18-55mm) measures the group photographs of vehicle, zoom lens measures the certain distance (70-300mm) photographs of vehicle and prime lens measures the close distance (40mm) photographs of vehicles. Lens-based Vehicle Classifier (LVC) is a method utilized for detecting the vehicle object. This method has 2 points for detecting the vehicle object, such as Strong Classifier and Estimation of Related distance. Strong Classifier is a rectangular feature providing specific indication to an image. Estimation of Related Distance measures 2 categories like Image Cropping [Vertical] and Image Cropping [Horizontal]. In obtaining vehicle object detection value, Strong Classifier was calculated using integral image. Integral images could calculate values accurately and relatively quickly by creating a new presentation of the image by using the value of the region previously scanned by a specific strong classifier. The value of the integral image was obtained by the sum value of the previous index, started by left top until right bottom.

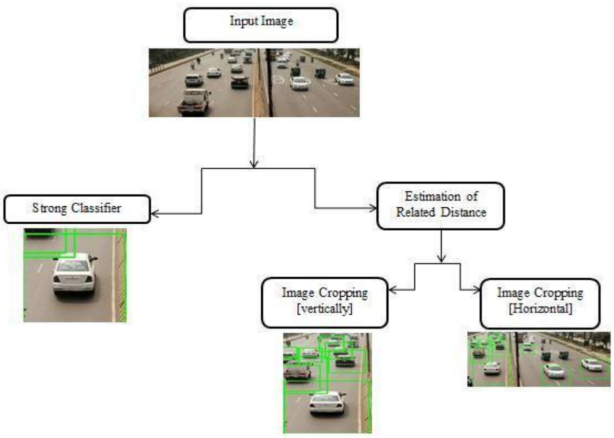

Fig.1 - LVC Method

B. Haar Cascade Classifier

Haar Cascade Classifier is a method utilized for detecting objects. This method has 4 points for detecting an object, such as a Haar-like feature, integral image, AdaBoost learning and Cascade Classifier. Haar-like feature is a rectangular feature providing specific indication to an image Haar-like feature offers high speed computation depending on the number of pixels inside the rectangle feature and not depending on each pixel value of the image. In obtaining object detection value, Haar- like feature value was calculated using integral image. Integral images could calculate values accurately and relatively quickly by creating a new presentation of the image by using values of regions previously scanned by specific Haar-like features. The value of integral image was obtained by the sum value of the previous index, started by left top until right bottom.

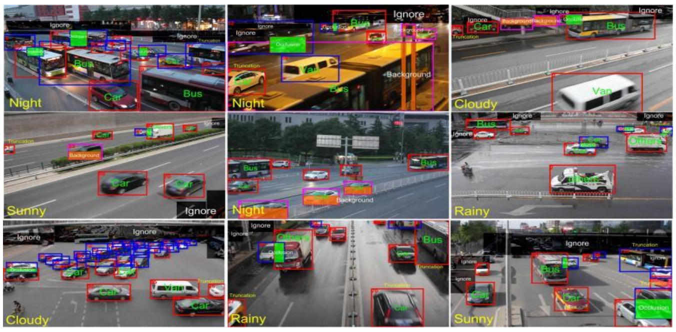

Fig. 2: Haar Cascade Classifier

A. Framework

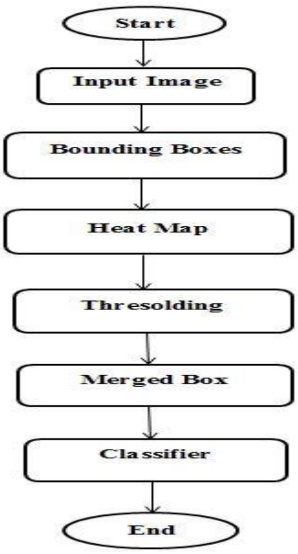

Fig. 3: Flowchart of the Inference Process to Detect the Vehicle

C. Overview

Fig. 3, discuss the framework of vehicle detection and how it works. First take the image from the DSLR camera as an image input that registers to the database. Then image output goes for the heat map that image pixels coordinate as a bounding box.[26] Then goes for the thresholding section. Thresholding observed the output image of the heat map. Then predict the detect object of the vehicle and it's probability at least 85% or less. Then image go for the merged box section. Merged box means all the images are merged and sent to the classifier section. In the classifier section apply Multiple Haar-like classifiers for V-J scheme-based approach.[4][5] And finally the image gone regressor section that means encoded the image range and gives the output in the display screen.

- At first take the image from the camera then register to the database. And this image passing is recorded from the database to framework. Aerial image of moving objects can be categorized by frame based and segmentation based. Image segmentation represents the complete shape of the objects. It means pixels with similar colors and attributes are together in image segmentation. In-put images are annotated pixel wise where captured by the camera of the vehicle. Image goes to bounding boxes where coordinates the pixel. Bounding boxes is a one to one correspondence class prediction. This prediction is also a smaller number of images.[27][30]
- Heat map is the output from the image of each pixel that coordinates to the bounding box. Heat map is representing the color as a matrix. Fractal and tree both maps are used in heat maps. When inputting an image to the system then heat map observed the image then sent to the bounding box where the image pixel is optimized to the map. Heat maps are used for bounding boxes that have a threshold of 85% probability of any class of object.[8][1][20]
- In the simplest implementation, the output is a binary image representing the segmentation. Black pixels correspond to background and white pixels correspond to foreground. In simple implementations, the segmentation is determined by a single parameter known as the intensity threshold.[34]
- When threshold is used in the bounding box then goes to the merged box. This approaches all the bounding boxes for their classifications of objects.[21][16]
- Multiple Haar-like classifiers are used in the V-J scheme-based approach. It's a strong classifier. This feature is drawn essentially for Haar basis functions for the image. Specific location for window detection at a different rectangular region. This region is rapidly used for the image called integral image.[12][23]
- The range regressors are trained after the training of classifier and bounding box regressor. Range regressors are encoded with the distance of meter objects. Range regressors when included the output of the image pixel are merged.[25]

III. EXPERIMENTAL RESULT AND ANALYSIS

The original goal was to detect mild vehicle damage using photographs that propose to use images obtained from the photograph and filter the edge to detect mildly damaged regions in the vehicles. Image edge result from vehicle undamaged part in addition to damage region. 2D projection-based model used to identify the vehicle undamaged part of the image edge.[13][32].

However, the vehicle body is very reflective and there is a large amount of inter object reflection in the photograph which is interpreted to damage. So, proposed a method for classifying reflection in photographs.

In this chapter, there is some limitation work to detect the reflection image edge in close photographs in vehicle panels. At last, it's possible to implement vehicle damage.[9]

A. Experimental Evaluation

Here, apply HAAR CASCADE features to detect the vehicles in the system. Also apply some algorithms to detect vehicles such as region-based approach, feature based approach.

Suppose to apply feature based detection module and the formula is-

For X axis- $F= \delta f(x, y)/\delta x = f(x, y)-f(x-1, y)$

For Y axis- $F= \delta f(x, y)/\delta y = f(x, y)-f(x, y-1)$

Here, proposed experimental evaluation for urban traffic areas is used for SVC and VDCS systems. And automatically detect vehicle damage by the VDCS system. This feature is testing both day and night mode environments. So, it’s a good result for tracking the classifications.

Now, experimental evaluation for nighttime vehicle detection is more effective for traffic monitoring. Image analysis are two modules such as daylight, and night light for detection vehicle damage.

Here, use gradient formula for image processing are-

g=median(ICS/IRS)

Here ICS means current image and IRS means reference image.

Finally, the vehicle crosses the detector line to detect the vehicles, and also easily to take images of the vehicles.

The Lens-based Vehicle Classifier and Haar cascade classifier are utilized for the object detection. Lens-based Vehicle Classifier method has 2 points for detecting the vehicle object, such as Strong Classifier and Estimation of Related distance. The Haar cascade classifier method has 4 points for detecting an object, such as Haar-like features, integral image, AdaBoost learning and Cascade Classifier.[14][31]

Fig. 4: Stay and Going Vehicle (Car & Bus) Detection by LVC & Haar Cascade

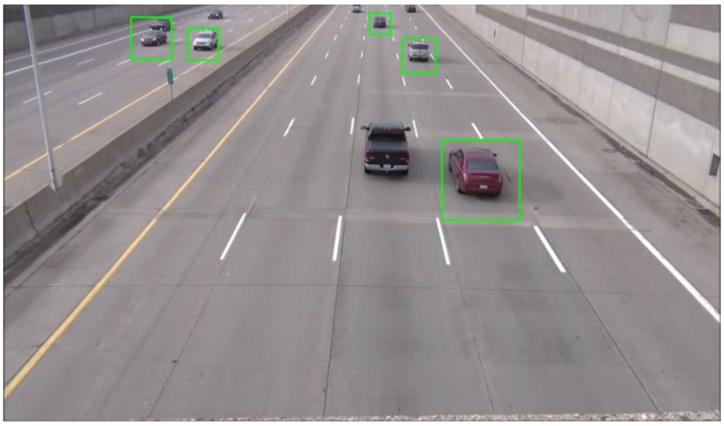

Fig. 5: Two-Way Vehicle (Car) Detection by LVC & Haar Cascade

Fig. 6: Vehicle (Bus) Detection by LVC & Haar Cascade

Fig.7: Vehicle (Bike) Detection by LVC & Haar Cascade

IV. LITERATURE REVIEW

Vehicle detection characteristics show the appearance of vehicle class detection. The image gradient-based process allows you to see the vehicle and distance with proper use of the camera. The blob position is successfully used in the frame and defines the blob detection. [6]. Blob detection is a technology that allows a system to track moving objects in a vehicle. Therefore, light and color must be defined together for blob detection and new blob detection. In the image, the connection from the blob to the system needs to know where the blob is distinguished between each frame. If the label is 1, the blob color is 0 [14] [17]. It consists of locating lane markers and adapting them to a lane model that tracks the position over time using an ego vehicle. Vehicle scenes where nighttime traffic is extracted and recognized through illuminated objects. The user interface design is intended to be accessible over the network using a card-based interface. Users often use google maps to find markers and annotated geographic locations displayed on their cameras. [9]. Corner detection is also one type of characteristic of computer vision systems where images can infer content. This computer vision is used for video tracking, motion, and image detection. It is also used for 3d modeling, registration, and image mosaicking of objects. It also overlaps with the topic of detection points [11] [13]. Photodetection is also a computer vision system based on known technology and uses common traffic light detection. In some disclosures of our monitor system, at least one image records vehicle data. This image analyzes the image data using the contour analysis of the traffic light assist system. This procedure is automatic vehicle support. [12]. All surrounding data is analyzed by the camera and the streets at the edge of the parking lot are also recorded. It also analyzes road markings, intersections, traffic lights or signs [18]. The vehicle can be recognized using a statistical method and prior knowledge of its characteristics. Object recognition can localize ego vehicles and formulate locations. In addition, it uses an improved tracking method to detect differences in overlapping objects between two adjacent frames. The vibe algorithm is fixed to the threshold method used for pixel backgrounds. Traffic videos are also used to classify foreground and background. Motion flows are still detected after extracting video pixels from moving objects. Motion flow in vector frames is also defined [11] [23]. Window detection is also a type of component of computer vision systems. This is related to a trained and tested pipeline. Window detectors protect window building classifications that provide direct motivation. Codebook vectors distinguish between window characteristics and fixed window class perspectives. It also recognizes the composition of the final scheme that is geometrically supplied [20] [22]. Region level, raw images, and vehicles are processed on three levels. This basic method of determining vehicle and area matching is suggested by going through an image sequence. It also sends the results of the highway scene to this method for demonstration purposes. We will also develop and briefly explain the camera function of the user-selected image. [15] [19]. Currently, monocular vehicle detection is presented to transfer similar image features such as symmetry, edges, etc. To establish robust functionality in vehicle detection [16]. Therefore, vision-based systems are important for the role of vehicle detection and for surveillance camera.

V. OBSERVATION AND CONCLUSION

A. Observattion

- They used lighting object extraction for vehicle detection in day time and invalid night time illuminate conditions.
- They are observed in urban area traffic environments because pure background is not available and critical situations being objects getting changed to remove the scene and also slow-moving objects.
- Multiple blob detection data showed the problem and compared the perfect location in the current frame with centroids of detection.
- Monocular images lack direct depth measurements.
- They observed robust features to locate the operator point that each patch distinctive to variation of scale.
- The detection line of pixels need to be occupied as 25% width, otherwise not to be occupied.
- Tracking road of contour length problem seen drift and zigzag.

VI. CONCLUSION

However, in this research, try to detect the problem of vehicle damage automatically using a camera by taking the damage scene of vehicle photographs. The objective of detecting vehicle damage by processing the video under rainy conditions. All the proposed algorithms are testing both city and urban environments. Here, All the feature analysis is complex and reduces some false detection. Proposed conceptual framework and framework seeing give good results, and also most efficient to apply this proposed framework. In this chapter, we discussed the research, and also overall project goals. And try to do much work by providing a problem, solution. Also need time to work on more unique research. This research using algorithm implementation is a various processing power. We hope that my work is going well and better in future research.

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