3D Post Estimation and Projection based Overaged Vehicle Detection
Using Various Geometric Techniques

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Abstract- Through picture detection we can determine the vehicles accident scene. This system determines the damage of a vehicle to the surface area. The vehicle user can upload some photographs of the damaged vehicle taken from a device and automatically assess the damage vehicle and do the processing by claiming to insurance [6]. This system may include a device (such as scanner) that generates data representative to the vehicle damage area. Since vehicles are shown reflective metallic bodies when the photographs are taken in such as uncontrolled environment can be expected there [2]. This system computes a device that processes the data to detect the vehicle damage items and also estimates the damage using this process. Therefore, we purposely try to use 3D CAD models for undamaged vehicles which are used to obtain ground truth information [6]. Here we present a 3D pose estimation method using image gradient information of the photograph and also the 3D model projection. Image edges of vehicle damage which are not present in the 3D CAD model projection. Moreover, we apply some geometric techniques for two view-points of photographs for image edges reflection [1]. All the vehicles can detect by surveillance camera [35]. Vehicle detection is a vision-based system that is a critical technology which plays an important role for active vehicle and also road video [34].

1 Introduction

Vehicle damage detection shown automatically through photograph since the vehicles accident scene is one of the most the challenging task. However, solving this problem is another challenging task for fascinating repertoire of computer vision that need to be context of address of challenging scenario. Since vehicles are shown reflective metallic bodies when the photographs are taken in such as uncontrolled environment can be expected there and apply standard computer vision techniques in the context [5]. Moreover, identity parts of the vehicles photograph to our proposition line to use 3D CAD model to register by using gradient based distance measure and also identify vehicles components to apply different segment method to help 3D model projection [3][7].

Different segment method such as image segment is one of the major problems in computer vision. Image segment techniques photograph pixel depends 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). The original parts and projected parts of 3D model do not match with the photograph vehicle damages. Image based segment method using for contour initial information for this 3D pose of projecting parts to the 3D model. Hence, we mainly focused on vehicles image and also reflective the surface of the vehicle body [8] [10].

Now, another problem is pose estimation in computer vision that application is used in vision image analysis. Generally, the process of pose estimation of obtaining an object part of location to its surroundings. Here, our work is also restricted for non-articulated object. 3D pose estimation required for application to application by

accuracy and nature. Here application depends on subset 3D pose parameters. Moreover, obtained to set image information to apply techniques structure from motion in different geometric view. Therefore, when this application completes then go to stereo matching image. Various features of the images are detected and also matched [4] [9]. Represent an important role for reducing traffic jam. This traffic route is more important to reduce traffic jam by using traffic light [34]. It's a major challenge for Robust vision-based system to detect vehicle on the road or highway in city or urban environment [35].

2 Literature Review

The characteristics of vehicle damage detection show the appearance of capturing the image vehicle class. Image gradient-based process can verify the vehicles and distance by properly using camera. Position of blob is successfully used on their image frame and defines detection of any blob [6]. Blob detection is kind of technique where the system can trace movement object of vehicles. Therefore, light and color must be defined together for blob detection and also for finding new blob. In the image blob must detect to the system connection where blob differentiate between each frame. If the label is 1 so its blob color otherwise 0 [14] [17]. Consist of locating lane marking and fitting to a lane model tracking their location temporally by using ego-vehicles. Vehicle scenes the night time traffic is extracting and detecting by lighting object. User interface design to be accessible through network with an interface of map based. Users are widely used Google maps for finding marks represented in camera and geographic locations annotated [9]. Corner detection is also one kind of features of computer vision system where the image in infer contents. This computer vision subsequently used in tracking video, detection motion

and image. And also used in 3D modeling object, registration and mosaicking image. It also overlaps the topic of detection point [11] [13]. Light detection is also computer vision system to known art and utilized generic detect traffic light. Some disclosure of our monitor system at least one image with records the data of the vehicle. This image now analyzes the image data by contour analysis for traffic light assistance system. This method is automated support for the vehicle [12]. All environment data analyzed by the camera and also recorded road of the parking edge. It also analysis road markings, crossing line and traffic lights or sign [18]. Vehicles can be detected based on prior knowledge of their characteristics by using statistical based method. Object detection can locate the ego-vehicle and formulate tracking. Also using improved tracking method for detecting the overlap object difference between two adjacent frames. Vibe algorithm is fixed for threshold method where is used in pixel background. It is also used traffic video for foreground and background classifications. Motion flow also detect after moving object video pixels are extracted. Also defined motion flow in vector frame [11] [23]. Window detection is also one kind of components of computer vision system. It is related to training and tested pipeline. Window detector defends on building classification of window where provided direct motivation. Discriminate the features of window and related to set window classes by code book vector. And also, configuration in geometrical to fed final schema recognize [20] [22]. Region level, raw image and vehicle are three level processing done. Proposed this base method for establishing correspond between vehicle and region, moves through a sequence of image. Also send highway scenes results to this method for demonstrate. Also develop camera features and briefly describe it for the image who selected by user [15] [19]. Nowadays, monocular vehicle detection is represented to transitioned similar image features like symmetry, edges and also sets robust features in vehicle detection [16]. So, vision-based and gradient-based system is important for vehicle detection role and also video application by surveillance camera [34] [35].
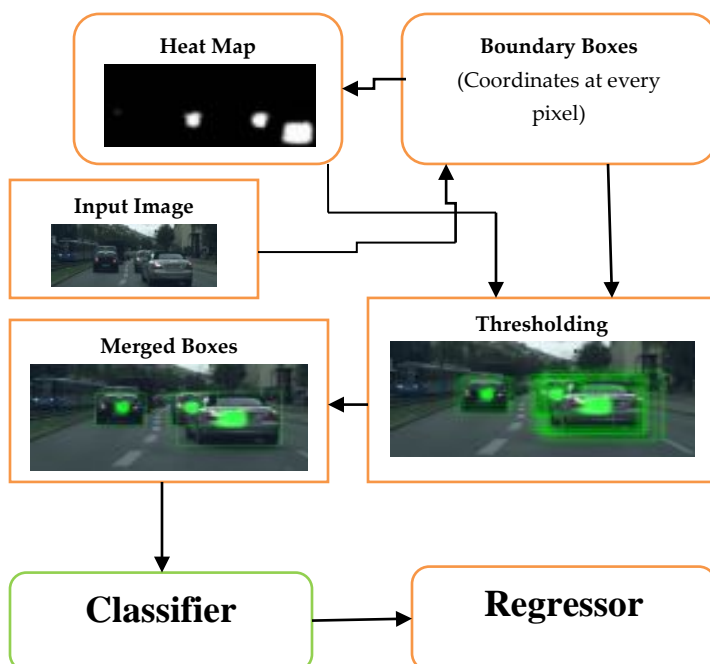
3 Proposed Conceptional Framework-

Fig: Flowchart of the Inference process to detect the vehicle.

3.1 Input Image- When image can take from the camera then image is register in database. So, image passing to the framework from the database where recorded. Moving objects from aerial images can be categorized by frame and segmentation-based. Image segmentation represents a more complete shape of the objects. Meanwhile, pixels with similar attributes and color are grouped together of image segmentation. Image pixel size is 72*72 and the resulted of spatial grid predictions. Input image are annotated pixel wise where the captured by the camera of the vehicle. Image goes to boundary boxes where coordinates the pixel. Boundary boxes are a one to one correspondences class prediction. This prediction is also less number of images. When image is tested and give to the thresholding and last to the merged image and at last gave to the user.

3.2 Heat Map- Heat map is the output from the image of each pixel that coordinates to bounding box. Heat map represents the color as a matrix. Fractal and tree both maps are use in heat map. When input image to the system then heat map observed the image then send to the boundary box where the image pixel is optimized to the map. Heat map are used for bounding box that that threshold of 85% probability of any class of object.

3.3 Thresholding- When the output image is in heat map then observed each pixel of image. Then send to the boundary box to predict. Boundary boxes are a one to one correspondences class prediction. This prediction is also less number of images. Heat maps are used for bounding box that that threshold of 85% probability of any class of object. It's an appropriate threshold for object that the predictions number considers less number. While the amount of image bounding box given the texted image to the threshold and predict the object several.

3.4 Merged Box- When threshold is used in bounding box then goes to the merged box. This approach is used for the entire boundary box for their classifications of objects. All the box scores are in intersection over union at the boundary box. At the end of threshold, the originates final output of image pixels and couldn't merge any boundary boxes. But cascade classifier approaches the boundary box to merge based there overlap by the parameter $\in$. This parameter is set for $\in= 0.35$. Range regressor when included the output of image pixel are merged.

3.5 Classifier- Multiple Haar-like classifier is used in V-J scheme-based approach. It's a strong classifier. This feature is drawn essentially for Haar basic functions for the image. Specific location for window detection at a difference rectangular region. This region is a rapidly using for the image called integral image. Also, this features weak classifiers for discriminative. The strong classifiers are generally generated the ad-boost learning process. It selects only trained classifiers for the preceding classifiers. It's a real time processing. Before use this V-J method the critical step builds a library both positive and negative images. In this section we classify more vehicles

image and also extracted to positive samples. All positive images are 40*20 pixels during their test. Measure distance directly with less computing resources, longer detection range than acoustic & optical sensor. The selection of entering and leaving points of vehicles will have a great influence on vehicle classification. Better performance for object shape and it's not sensitive change by using HOG features. Moving distance of potential vehicle bounding box in a vertical direction between two successive frames depend on the vehicle speed. Bounded the lane area which is called RAI (Road Area Image). And need to verify these so need first lane marks. Traditional object detection algorithms propose candidates in the point cloud and then classify them as objects. Using detection high frequency to detect vehicle more than second. Also, some algorithm is described to help for vehicle detection.

3.6 **Regressor-** Labels for boundary box by regressor where constructed for the structure mask for using classifications. It's encoded the pixel location. It's encoded to the location as x1=y1=x2=y2=0 and ignored during training the output of boundary boxes regressor.
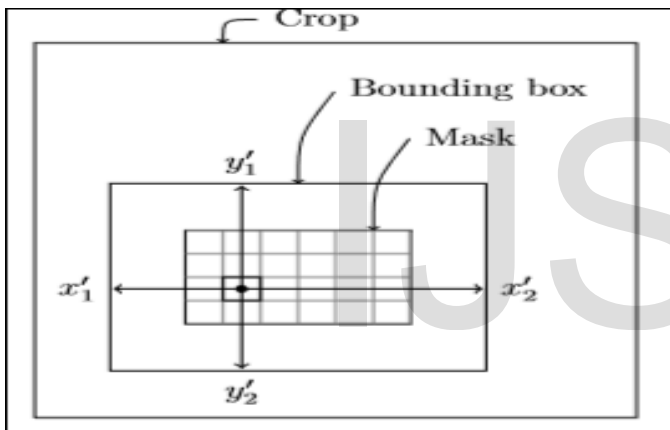
And also used for this function-

$$Cc\ (p, p\hat{}) = sum\ (pi - \hat{}\ pi)2$$

$$Cb\ (y, y\hat{}) = sum\ (yi - \hat{}\ yi)2$$

Here p and y are output for the classifier and regressor to labels of p and y. And its range 0 to 1. Regressor output pixels vary 10 to 200.

The range regressor is trained after the training of classifier and boundary box regressor. Range regressor is encoded with the distance of meter objects. Range regressor when included the output of image pixel are merged.

4. **Proposed Experimental Evaluation**

Here we apply the hog feature approach the system to detect the vehicles. Also apply some algorithm for detecting the vehicles such as

region-based approach, feature based. Detect the image, bob and also many things.

Suppose we apply feature detection module approach and the formula we follow-

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)

We proposed experimental evaluation for urban traffic is used SVC and VDCS system. It manually used for vehicle to detect the damage with image and also classification observed by SVC system. And also detect automatically damage vehicle by VDCS system. This feature can be tested real camera footage day and light environment. So, it to tracking the classification results [37].

We proposed experimental evaluation for vehicle detection night time is a good effectiveness for traffic monitoring. We see the image analysis is two modules to detect day, light or night, light. The entire moving object is based on operator threshold.

Also use the gradient formula for image processing-

$$g= median\ (Ics/Irs)$$

Here Ics mean current image and Irs mean reference image.

There are also many algorithms to detect the vehicles. Also, some virtual line for detecting line, start line, middle line, end line.

Here we see the line and also the detector area. When vehicles cross the line it easily takes the image and also detect the vehicles.
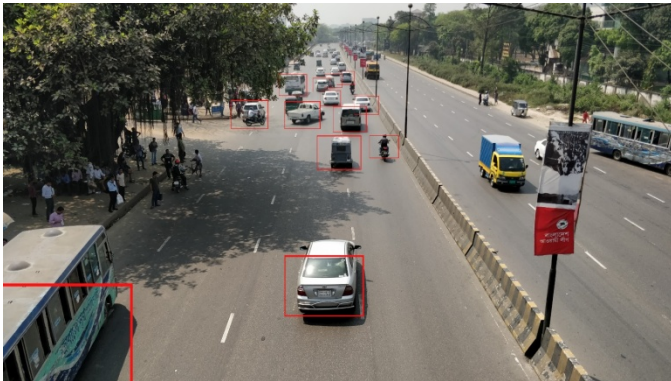
Image 1: Detecting some vehicles in day light
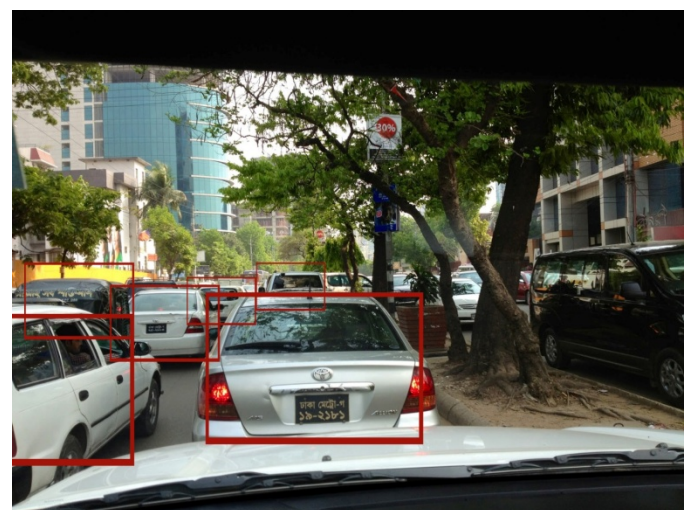
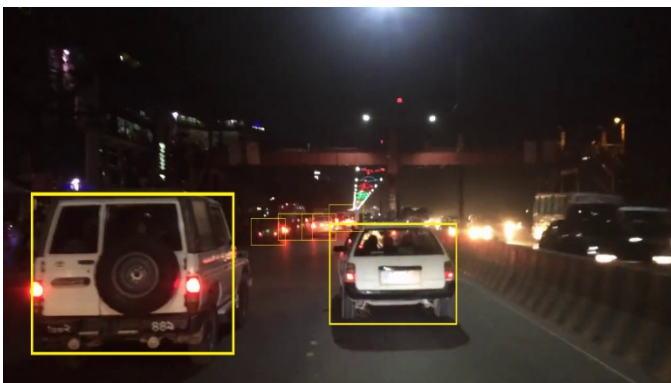**Image 2: Detecting some vehicles in night mode**

5 Discussions

Any useful conclusion seems very difficult to draw because training database is quite small. Image gradient-based methods to detect image using camera by checking the camera configuration. Similarly, the scale of measurement is being dependent on distance measure. Mechanism finds blob position are analyzed the same level and also incremented the vehicle count successive by frame of image [30]. Vehicle scenes the night time traffic is extracting and detecting become invalid in illumination conditions of moving object from traffic image. Tracker proposes a simultaneous tracking and recognition method using vehicle classification in IR-based video sequences. User interface designed to be accessible through internet-based browser. Wald's sequential training iterative gradually builds a more complex sequential classifier of negative samples [15] [18]. Detect vehicle damage by process the video under rainy conditions. The entire proposed algorithm is for testing both city and urban environment. Here we use MATLAB algorithm for theoretical value [34] [35].

6 Conclusions

However, in this paper, we try to detect the problem of vehicle damage by automatically using camera by taking the damage scene of vehicle photographs. The objective of detecting vehicle damage by processing the video under rainy conditions. The entire proposed algorithm is testing both city and urban environment. Here we use MATLAB algorithm for theoretical value. All the method analysis is complex and reduces some false detection. Proposed conceptional

framework and framework seeing give good results and also most efficient to apply this proposed framework. In this chapter we discussed our research and also overall project goals. Moreover, we tried to do much work by providing problem solution. We also need time to work more unique in this research. This research using algorithm implementation is a various processing power. We hope that our work is going well and hopefully it will be better in future thesis research.

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