DEEP LEARNING APPROACH MODEL FOR VEHICLE CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK

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Abstract - *The Vehicle detection is used to identify the vehicles in any video or image file. The process of detection of vehicles includes the object detection by considering the vehicles as the primary object. By taking the images form aerial or horizontal view and from road or parking using surveillance cameras, the detection process can be initiated. A vehicle recognition method based on character-specific extremely regions (ERs) and hybrid discriminative restricted Boltzmann machines (HDRBMs) is performed by top-hat transformation, vertical edge detection, morphological operations, and various validations. It proposed a novel algorithm to identify the density of vehicles by using the vehicle detection and classification algorithm by implementing the hybrid deep neural network over the huge dataset of video and images that are obtained from the satellite images. For feature extraction Non-negative Matrix Factorization (NMF) and SVM compression is used. Where, compression is used to increase the response time for detection and classification. The proposed model has been designed for the vehicle position identification as well as the vehicle type classification using the deep neural network. The proposed model has been tested with a standard dataset image for the result evaluation.*

Key Words: *Negative Matrix Factorization, hybrid discriminative restricted Boltzmann machines, extremely region, and classification method*

I. INTRODUCTION

Vehicle detection and classification plays crucial role in traffic monitoring and management. The application of vehicle detection and classification is very vast. Vehicle detection is used on roads, highways, parking or any other place to detect or track the number of vehicles present on the spot. This will help the surveillance to judge the traffic vehicles, average speed and category of vehicle. There are number of object detection techniques are available to detect and classify them. Object Detection is a method that finds instances of world objects like pedestrians, faces, vehicles and buildings in pictures or in videos. It uses extracted features and therefore the learning algorithms for recognizing the instances of object class. Applications that uses object detection method are image retrieval, security, surveillance, automatic vehicle parking systems. Object detection uses numerous models: Feature primarily based on object detection, SVM classification, and Image segmentation. There are many classification algorithms that are being utilized for the main aim of the vehicular detection and classification. Primarily we are using the probabilistic, non-probabilistic or square distance based object detection and classification mechanisms. The classification technique like Support Vector Machine (SVM), co-forest , k-nearest neighbor, neural network, random forest etc are being utilized for the vehicular detection and classification. Using neural network one may also learn and reconcile advanced non-linear patterns. Neural network possesses artificially intelligent bio-inspired mechanism that may be helpful for feature extraction. Neural network is a feedback network wherever the feedback is forwarded to neural network.

The high pace development of technologies Predominantly image or video processing techniques have enabled a number of application scenarios. Visual traffic surveillance (VTS) based intelligent transport system (ITS) is one of the most sought and attractive application and research domains, which has attracted academia-industries to enable better efficiency. The significant application prospects of ITS systems have motivated researchers to achieve a certain effective solution. An efficient vehicle detection and localization scheme can enable ITS to make efficient surveillance, monitoring and control by incorporating semantic results, like "X-Vehicle crossed Y location in Z direction and overtaking A Vehicle with Speed B". Considering these needs, in previous works [1,2], vehicle detection, tracking, and speed estimation model were developed. However, the further optimization could enable more efficient ITS solution. Developing a novel and robust system to detect and classify the vehicle simultaneously can be of paramount significance.

Applications of vehicle detection:

- Vehicular density evaluation in the urban areas for the traffic shaping
- Automatic parking system to decide which vehicle type if allowed
- For automatic counting and information gathering about the vehicles coming in or going out of the parking lots
- Aerial surveillance of the vehicular objects in the urban areas
- Vehicle tracking on the roads across the countries

II. LITERATURE SURVEY

Yi-Ling Chen et. al. [1] Proposed an intelligent and novel Video Surveillance System for self driven vehicle detection technique and Tracking in Clouds and the installation of surveillance of video surveillance cameras is done to keep the vehicle dataset containing the vehicles. For detecting any suspicious threat, human interaction is needed. There are lots of other potential security problems that are detected using the help of automated methods. The methods used to detect and classify the vehicles when uncontrolled environment is there. Proposed models performance can be evaluated by improvement in accuracy.

Thomas Moranduzzo. [2] Has proposed the UAV (unmanned aerial vehicle) detection technique for images with a catalog-based approach. Existing systems work with monitoring operation that some areas are classified to make the detection of vehicle faster and robust. Concurrently, to extract features of HOG, filtering operations are used in vertical and horizontal. Then the orientation value of possible 36 directions which is actually the vehicle points that is computed by searching the highest value of similarity measure and in the end avoids duplicity, as unmanned aerial vehicle images data has very high pixel resolution so there may be a possibility that a car may be identified more than once. So, in the end of HOG extraction same car are merged. The accuracy performance of proposed system is higher number of possible 36 directions of movement.

Sayanan Sivaraman.[3] has proposed an Integrated lane method for vehicle tracking, detection and localization. Proposed system developed the Synergistic approach to fuse the vehicle tracking and lane for the assistance of driver. The result of proposed model is obtained by the improved performance of vehicle and lane tracking. Detection of vehicle has achieved an adequate accuracy level.

Sebastian Tuermer [4] has proposed Airbone vehicle detection in very dense urban location by using the HOG features with Disparity Maps. The main objective of proposed model is to analyze and describe the chain of integrated real time processing. The input dataset consist the two subsequent images, a global DEM, exterior orientation data and a database. Similar or overlapped areas are extracted by region growing algorithm. After then the remaining parts classification of input data is conducted that is based on features of HOG. This will produce the faster and accurate results.

Sayanan Sivaraman [5] has proposed a model for looking at vehicles on the road. Authors discusses the detection of vehicle based on vision, behavior analysis and tracking. They define the algorithm for on road vision based detection of vehicle and also the classification algorithm. They classify the branch of vehicles which further refers to spatiotemporal measurements and trajectories tracking. The proposed model achieved improvement with high accuracy that is effective with and trajectory tracking and spatiotemporal measurements.

Thomas Moranduzzo [6] has proposed an algorithm for Automatic Car Counting method for UAV images. Proposed system includes multiple steps i.e. the first step is used for the asphalted zones screening. So that the particular area where vehicle is detected is restricted and may reduce the false alarms. By using this method feature extraction is done more accurately and effectively. In the end, the key points extracted from vehicles belongs to same vehicle is fused together to achieve "one key point -one car". The accuracy result of positioning for vehicles counting and the cars within 2cm can be obtained using real UAV scene.

Chen, Bo-Hao, and Shih-Chia Huang [7] have proposed neural networks primarily based on extraction of moving vehicles for surveillance to intelligent traffic. Proposed model uses the moving vehicles that can be detected in any resolution range

III. PREVIOUS IMPLEMENTATIONS

Vehicle detection is defined as detecting the vehicles on the basis of parameters such as color, shape and size. Vehicles are detected usually by extracting the vehicle queues from the satellite images. The vehicles can be detected with the help of neural network i.e. convolutional neural network. The complete system is trained in order to classify, locate and detect the objects in images. Hence this can improve the accuracy of classification, detection and localization. The network can be applied at multiple locations in the image using the sliding window technique. Then the system is trained to produce prediction of the size and location of bounding box. A technique is defined to perform object localization with convolution network based segmentation.

The above table has been recorded with the elapsed time for the vehicle recognition and vehicle detection transactions performed in the proposed model. The average classification time has been found around 234 seconds in the all 13 transactions to recognize the 13 vehicular objects in the simulation. Also the detection time has been recorded from the simulation, which has been recorded around 6 seconds on an average for the all 13 transactions. The proposed model have correctly identified the all of the vehicular objects in the given test image for the experiments. The experimental results have shown the effectiveness of the proposed model in the case of vehicle detection and classification. The proposed model has been proved to be efficient and robust object classification system. In the future, the proposed model can be applied on some of the standard vehicular dataset. The proposed model can be also tested with the video data for the vehicular detection and classification purposes.

RESEARCH GAPS

- The existing model evaluates the overall density of the vehicles but does not classify them in order to evaluate the traffic more effectively over the urban roads.
- The existing model for the vehicle detection lacks in analyzing the density over the roads after classifying and identifying the specific type of the vehicles in order to prepare the traffic shaping and planning to reduce the congestion across the busy roads in the urban areas.
- The busy tunnels, where the congestion occurs almost every day, the traffic shaping method can be applied to allow the computed number of vehicles per day in order to reduce the traffic.
- The block-wise processing for the estimation of the vehicular class with neural network makes the whole process slower and tedious due to the inclusion of the slider window function. The execution time can be reduced by using the reduced feature component with fast classification.
- The existing models are capable of vehicular detection only and do not produce any of the time series based vehicular traffic density and analysis. The exiting model does not perform any vehicle classification based on the size like whether the vehicle is heavy or light. The system does not create the vehicular analytical framework for the vehicular detection, classification and time based analytical study.

IV. SYSTEM IMPLEMETNATION

The proposed solution aimed the vehicle detection and classification are the models utilized primarily for the vehicular traffic surveillance, data collection and relevant applications. The vehicular detection and classification models require the hierarchical approach for the template matching based object detection with probabilistic or non-probabilistic classification algorithms. There are several challenges which occur for the implementation of the state of the art system for the vehicular classification and modeling. In this paper, we have proposed the new age model for the vehicular detection and classification with high density vehicular database. The proposed model is being developed over the low frame rate cameras which two or three frames per second. The proposed model will evaluate the vehicular type and classify them properly in order to evaluate the traffic density categorized in the vehicular type. The study obtained from the proposed model would be utilized for the traffic management policy making by analyzing the rush hours and the reasons behind the congestion during the rush hour. The optimal steps could be taken during the rush hours, such as the heavy weight carriers can be stopped from entering the congested highways to maximize the average traffic movement speed. The proposed model is expected to improve the performance of the vehicular classification over the performance measures of precision, accuracy and recall. In the future, the proposed model would be realized to achieve the goal of vehicular classification and the detection in the captured frames from the traffic surveillance cameras.

- Improved camera calibration method by detection of two vanishing points – camera calibration error reduced by 50 %.

- Novel method for scene scale inference significantly outperforming automatic traffic camera calibration methods (error reduced by 86 %) and also manual calibration method (error reduced by 19 %) in automatic speed measurement from a monocular camera.

- The results show that the automatic (zero human input) method can perform better than laborious manual calibration, which is generally considered accurate and treated as the ground truth. This finding can be important also in other fields than only in traffic surveillance.

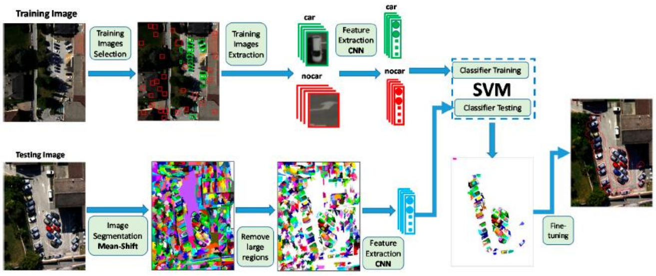

Fig: System Architecture

The proposed method is illustrated in Figure 1, and is based on the four main steps. First, the image is over-segmented into a set of regions by means of the Mean-shift algorithm. These regions are taken as the likely locations to inspect for cars since one region—or a small group of them—may represent a car. The second step is devoted to the feature extraction process, where a window around the candidate region is given as input to a pre-trained CNN for feature extraction. Third, a linear SVM classifier is trained to classify regions into either a “car” or “no-car” class. The result is a binary map representing a segmentation of the UAV image into “car” and “no car” classes. Finally, the binary map is fine-tuned by morphological operations and the further inspection of isolated cars.

$$\hat{f}_{h,K}(\mathbf{x}) = \frac{c_{k,d}}{nh^d}\sum_{i=1}^{n} k\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{h}\right\|^2\right) \text{ -------------- (1)}$$

We considered the Mean-shift algorithm in our study, as it is a robust feature-space analysis approach that can be applied to discontinuity preservation, smoothing, clustering, visual tracking, mode seeking, and image segmentation problems. The theoretical framework of the Mean-shift is based on the Parzen window kernel density estimation technique, where for a given set of data samples $\{Xi\}_{i=n}$ d-dimensional space, the kernel density estimator at sample X is given by, Where $c_{k,d}$ is a normalization constant, h is the bandwidth, and $k(.)$ is the profile of the kernel

The Mean-shift procedure is an efficient way of locating these zeros without estimating the density, since images are represented as a spatial range joint feature space. The spatial domain denotes the locations for different pixels, whereas the range domain represents the spectral signals for different spectral channels. Thus, a multivariate kernel can be defined for joint density estimation:

$$K_{h_s,h_r} = \frac{\rho}{h_s^2 h_r^d} k\left(\left\|\frac{\mathbf{x}^s}{h_s}\right\|^2\right) k\left(\left\|\frac{\mathbf{x}^r}{h_r}\right\|^2\right) \text{ ----------- (2)}$$

Where ρ is an normalization parameter and h = [h_s, h_r] at is produced by Mean-shift filtering. The use of the Mean-shift segmentation algorithm requires the selection of the bandwidth parameter **h**, which (by controlling the size of the kernel) determines the resolution of the mode detection. It can be noted that the Mean-shift algorithm cannot segment very large resolution images; however, we can divide the large image into smaller parts, apply the Mean-shift algorithm to each part separately, and combine the result.

Fig : 1(a) original image

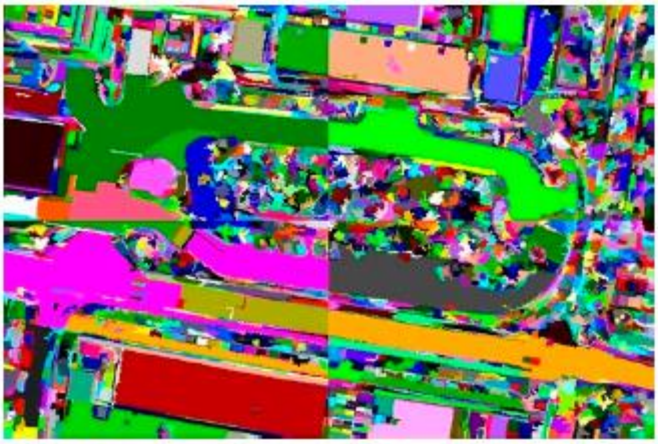

Fig 1(b) Mean Shift Algorithm

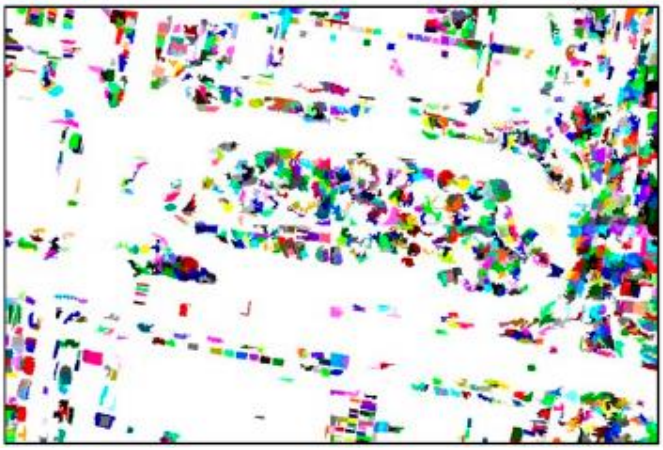

Fig: 1(C) Regions Filtering

Nevertheless, one advantage of the Mean-shift algorithm is that it provides an opportunity for the early elimination of large areas of the image based on the size of large regions. For example, as shown in Figure 1b, most of the asphalt regions (like roads and parking lots) are segmented in large regions, which can be easily removed from the search space automatically by including only regions that have a width or height close to the average car size in the image. By applying this simple technique, only the regions shown in Figure 1c needed to be included in the search space.

Mean Shift Algorithm

A kernel is a function that satisfies the following requirements:

1. $\int_{R^d} \phi(x) = 1$

2. $\phi(x) \geq 0$

Some examples of kernels include :

1. Rectangular $$\phi(x) = \begin{cases} 1 & a \leq x \leq b \\ 0 & else \end{cases}$$

2. Gaussian $\phi(x) = e^{-\frac{x^2}{2\sigma^2}}$

3. Epanechnikov $$\phi(x) = \begin{cases} \frac{3}{4}(1-x^2) & if\ |x| \leq 1 \\ 0 & else \end{cases}$$

Kernel Density Estimation

Kernel density estimation is a non parametric way to estimate the density function of a random variable. This is usually called as the Parzen window technique. Given a kernel K, bandwidth parameter h, Kernel density estimator for a given set of d-dimensional points is

$$\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

Feature Extraction

Deep CNNs are composed of several layers of processing—each containing linear as well as nonlinear operators—which are jointly learnt in an end-to-end way to solve specific tasks .Specifically, deep CNNs are commonly made up of convolution, normalization, pooling, and fully Connected layers. The convolution layer is the main building block of the CNN, and its parameters consist of a set of learnable filters. Each filter is spatially small (along width and height), but extends through the full depth of the input image. The feature maps produced via convolving these filters across the input image are then fed into a non-linear gating function such as the rectified linear unit (ReLU). Next, the output of this activation function can be further subjected to normalization (i.e., local response normalization) to help in generalized.

Region Classification with a Linear SVM

During this step, we went through all regions in the image and checked if they represented a car. To do this, we extracted a window surrounding the concerned region and passed it to a pretrained CNN for feature extraction. Next, the feature descriptor was classified as either a “car” or “no-car” using an SVM classifier. This last step was trained on a collection of image samples for both classes. The set of positive samples was manually annotated in the training images, while the set of negative samples was randomly selected from the remaining areas of the training images. The window surrounding the concerned region could be defined in two ways:
(1) as the bounding box of the region,
(2) as a window centered at the centroid of the region with a given size. By inspecting the regions could clearly see that for many small regions that represented parts of the car (like the roof or the front windshield), taking the bounding box may not have contained sufficient car features for high quality detection. The second option should yield better results. Furthermore, cars in images can have any direction; thus, if rectangular windows are us

Fine-Tuning the Detection Result

The result of Step 3 was a binary map showing all regions that were classified as car regions. In this last fine-tuning step, we cleaned up the final map by applying three extra operations: (1) applying a morphological dilation operation on the detection map to smooth out region boundaries and merge close-by regions; (2) filling holes that may have appeared in detected regions; and (3) inspecting small isolated regions to improve the detection of isolated cars and potentially reduce false alarms. the results show that the method achieved a high true positive (TP) rate; however, there was also a relatively high false positive (FP) rate. This was due to some small isolated regions of the image containing car-like signatures. First, it was noted that cars were usually parked in groups close to each other, and most regions detected as cars were next to each other. Hence,

such regions merged into larger regions in the final mask, and only a few isolated regions remained spread across the image. Some examples of this small isolated region where it is clear that some of them indicate a real parked car in an isolated area, and that there were many false positives. To remove some of these false positives

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Fig: Detection results in test image

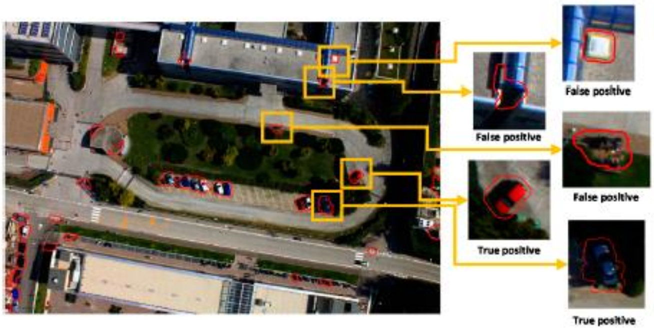

Fig : Samples of small isolated regions where some are isolated parked cars (true positive) while others are false positives.

CONCLUSION

Developed an efficient method for the detection and counting of cars in UAV images, which has the following novel features: (1) reducing the search space significantly compared to the sliding-window approach by using the Mean-shift algorithm; and (2) the use of deep learning approaches to extract highly descriptive features without the need for huge amounts of training data through the use of pre-trained deep CNN combined with a linear SVM classifier. The experimental results on five UAV images show that our method outperformed state-of-the-art methods, both in terms of accuracy and computational time. However, despite the high capability of the method to detect car presence and numbers, it still has a high FP rate

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