Supervised Appearance Model with Neural Network for Vehicular Object Classification

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Abstract— The object detection is the procedure to evaluate the position of the objects in the given image data by analyzing the template data against the input image. The vehicular object detection involves the feature discovery and location marking in the given image matrix. The fore process may involve the object classification for the determination of the category of the evaluated object in the image matrix. The object classification model is considered as the primary process for the object category determination and discovery. In this paper, the supervised appearance similarity model has been utilized as the template matching scheme for the evaluation object appearance in the input image data. The template matching scheme evaluates the location of all of the discovered objects in the input matrix, which are marked using the blue boxes for the visualization. The deep neural network (DNN) classification model has been utilized for the purpose of category evaluation of the detected objects. The feature minimization in the proposed model has been also achieved using the non-negative matrix factorization (NMF) for the realization of the quick response vehicular detection and classification system. The neural network classification model also utilizes the training data for the vehicular class evaluation. The various performance parameters have been obtained from the proposed model results after the deep evaluation. The experimental results have proved the higher efficiency of the proposed model in comparison with the existing models. The proposed model has obtained 97.25% accuracy which is way higher than the existing models.

Key words: Neural Network Classification, Time Efficiency, Deep Neural Network, Supervised Appearance Model

I. INTRODUCTION

Today the need to understand the number and the type of vehicles on roads is becoming important to record the traffic data. In todays real world, there is a demand for traffic monitoring those areas which are densely populated. The traffic flow on main roads is measured by induction loops, bridge sensors and stationary cameras. The traffic on smaller roads is monitored and information about the on road parked vehicles is not collected. Thats why new applications like traffic monitoring and vehicle detection have achieved attention on international conferences. The presented approach focuses on detection of vehicles from vehicle queues with the help of satellite imagery.

To monitor the traffic, vehicle detection and classification plays a very crucial role. Vehicle detection is used on highways, parking areas, roads and many other places to detect the vehicles on the spot that helps to judge the traffic density. the type of vehicles, average speed. For detection and classification, number of object detection techniques is available. Many classification algorithms have been utilized for vehicle detection and classification. The techniques-probabilistic, non-probabilistic or square distance based object detection and classification mechanisms are used. Neural network is an artificially bio-inspired mechanism which helps in feature extraction and is also a feed forward network. To visualize the overlapping regions, individual neurons are tiled during this network. Multilayer preceptrons are designed to reduce the amount of preproccessing.

This paper proposes the fusion of neural network along with non-negative matrix factorization with other image processing techniques like image vectorization, image de-noising that have been used for vehicle detection and classification. For vehicular classification over imagery data, neural network is used. This paper proposes the new model for vehicle detection and classification with high density vehicular database. These approaches evaluate the type of vehicle and classify the vehicle to evaluate traffic density categorized in vehicle type (whether the vehicle is light or heavy). In this paper, model is designed for traffic management by analyze the rush hours. The performance of vehicle classification over the performance measures of accuracy, precision, recall is improved.

In this section of introduction section (1) the overview of the vehicle detection and classification method has been discussed. The rest of paper has been organized as follows: Section (2) discusses the related work on vehicle detection. Section (3) describes the experiment analysis of proposed model. Section (4) describes the result and its analysis. Finally the Section (5) concludes the paper.

II. LITERATURE REVIEW

Sayanan Sivaraman.[4] has collectively worked on an integrated lane method for vehicle detection, tracking and localization. This model uses the approach named as Synergistic approach to combine the vehicle tracking and lane for the assistance of driver. Performance of vehicle and lane tracking is improved in this proposed model. The result of this model is that the detection of vehicle has achieved an adequate accuracy level.

Jazayeri et al. [1] has proposed the detection and tracking of vehicles in car. The motive behind this is safety, target tracing and auto driving. This model tells about the localization of target vehicles in video. Feature extraction is done in a 1D profile manner to speed up the tracing and identification of vehicles. HMM (Hidden Markov Model) is defined to separate the target vehicles from background in a manner so that the vehicles can be tracked probabilistically. Three type of vehicles of low level features are used for reliable vehicle detection i.e. corner detection, line segment detection and intensity peak detection. In order to increase the speed of processing for real time target tracking and to achieve the robust results, the intensity or color is projected vertically in each video frame. The results show the robustness and effectiveness of the design and implementation of the system. In real time, the computation is done so that real time processing is possible for vehicle-borne cameras.

Sivaraman et al.[16] has described a novel approach for localization of vehicles and tracking of vehicles that combines stereo- vision to the monocular vehicle detection. This model acquires the information from stereo- vision for 3D localization and then obtains monocular frames that are synchronized and then calculate the depth maps. By using a vehicle detector the system detects the vehicles in image plane. Then the system localizes vehicles by using image coordinates of detected vehicles. The result of this system is that, the 3D location of vehicle is solved by using stereo- vision. Firstly the state of the vehicle is determined and then by using Kalman filtering vehicle is tracked. The complete system takes 46ms in the processing of a single frame.

Song et al. [9] described a system for vehicles based on sensor network. To detect the unauthorized movement of the vehicle and tracking of the stolen vehicles SVATS is used. Alarm systems or tracking systems have been defined as the rate of theft of vehicle is high. Such systems have disadvantage like high cost and high false alarm rate. In this system, the vehicles that are parked in same parking area builds a sensor network, after that it monitors and identify the vehicle thefts and this can be done by detecting the unauthorized movement of vehicle. This system also defines the various technical issues such as theft detection and movement detection, connectivity management and intra- vehicle networking.

Chen, Bo-Hao, and Shih-Chia Huang [8] have proposed probabilistic neural network based on extraction of moving vehicles for surveillance to intelligent traffic. In this, the proposed model uses the moving vehicles that can be detected in any resolution range.

Sayanan Sivaraman [6] has proposed a model for looking at vehicles on the road. Authors discusses the detection of vehicle based on behavior, analysis, vision and tracking. This system defines the algorithm for on road vision based detection of vehicle. The proposed model classifies the branch of vehicles which further refers to spatiotemporal measurements and trajectories tracking. The proposed model achieved improvement with high accuracy that is effective.

III. EXPERIMENTAL DESIGN

The proposed model is the hybridized model of the deep neural network, non-negative matrix factorization and supervised appearance model for the vehicle classification and detection in the input image matrix. The proposed model has been designed as the quick response system for the faster evaluation and the robust performance. The proposed model core is entirely based upon the deep neural network with multi-layered processing. The Deep Neural Network for the standard backpropagation algorithm can be discriminatively trained under the specific model requirements. The neural network weight updates can be possibly calculated using the stochastic gradient descent using the formula defined in the following equation:

$$W_{ij}(\mathrm{t+1}) = W_{ij}\ (\mathrm{t}) + \ n\frac{\partial C}{\partial w_{ij}}$$

Where n is the learning rate, C is cost function. The choice of cost function is based upon various factors like learning model type of unsupervised, supervised, etc or the neural activation function. The standard cost function is used for the cost evaluation is the softmax function, which can be defined as the following:

$$p_j = \frac{\exp(x_j)}{\sum_k \exp(x_k)}$$

Where p_j is the class probability, x_j and x_k are the total input to units j and k. The cross entropy is defined as the

$$\mathrm{C} = - \sum d_j \log{(p_j)}$$

Where d_j represents the target probability for output unit j and p_j is the probability output for j after applying the activation function.

A. Algorithm 1: Deep neural network based classification for vehicle classification

1) *Begin*
2) *Load the Image.*
   a) Im= selectionWindow(FolderName, FileName);
   b) Im=readImage([FolderName FileName]);
   c) Return Im.
3) *Apply Median Filter on Im.*
   a) Imf = median2d(Im,windowSize, Intensity);
   b) Return Imf.
4) *Apply Nonnegative matrix factorization on Imf.*
   a) Nmf = nmf(Imf, [colSize rowSize]);
   b) Return Nmf{1,2,3…..N}.
5) *Perform Vectorization over Nmf and Imf.*
   a) I = 1;
   b) Imf_d1 = Imf(:,:,I);
   c) Imf_v1 = Imf_d1(:);
   d) I = 2;
   e) Imf_d2 = Imf(:,:,I);
   f) Imf_v2 = Imf_d2(:);
   g) I = 3;
   h) Imf_d3 = Imf(:,:,I);
   i) Imf_v3 = Imf_d3(:);
   j) Nmf(1,2,3…. N) = Nmf(:);
   k) VecData{1,2,3… N} = {Imf_v1 Imf_v2 Imf_v3 Nmf(1,2,3…N)};
   l) Return VecData{1,2,3…..N}.
6) *Locate the feature locations in the image on VecData.*
   a) LocationVector(id, x^n, y^n) = getLocation(VecData, {ApperanceModel});
   b) LocationArray{(X1, Y1), (X2, Y2)………(Xn, Yn)} = LocationVector(id, x^n, y^n)
   c) Return LocationArray{(X1,Y1), (X2,Y2), (X3,Y3) ……. (Xn,Yn)}.
7) *Classification of the objection types Im and Location Array.*
   a) ClassifiedData{ t1, t2, t3 ….. tN} = nn (TrainData, LocationArray(Xn, Yn))
   b) Return ClassifiedData{ t1, t2, t3 ….. tN}.
8) *Mark classification on Imf with Classified Data.*
9) *End*

IV. RESULT ANALYSIS

The proposed model has been designed for the vehicular detection and classification in the given image selected using the selection dialogue. The vehicular detection model has been based upon the template matching technique using the matrix differentiation model. The results have been obtained in the form of various performance parameters such as recall, precision, positive predictive value and the overall accuracy. The obtained performance parameters have been listed in the following table (table 1):

Performance Parameter	Parameter Value
Recall	96.10%
Precision	95.08%
Positive Predictive Value	97.50%
Accuracy	96.41%

Table 1: The parametric results obtained from the simulation

The vehicular object detection model is entirely based upon the supervised model based matrix appearance similarity, which selects the object with the highest similarity of the determination of the object position. The vehicle region selected in the earlier step is extracted as the region of interest (ROI) for the further evaluation. The deep neural network has been used for the network classification, which primarily classifies the data in two primary categories of heavy and light vehicles. The computational complexity of the proposed model has been evaluated in the form of time complexity parameters. The time complexity has been evaluated for the object detection and classification separately. The obtained values of time complexity have been shown in the following table (Table 2):

Index	Average time for classification	Average time for detection
1	2.49	2.73
2	3.45	2.23
3	3.98	4.72
4	3.51	1.00
5	3.59	1.18
6	3.94	2.73
7	3.20	1.23
8	4.35	3.59
9	4.20	3.57
10	2.86	2.26

Table 2: The time complexity analysis of ten images from the dataset

The following figure 1 visualizes the values obtained under the table 2. The average detection time is usually lower than the average classification time, whereas in some of the odd cases the classification model runs quicker than the detection model due to the smaller size of the vehicular objects in the given image.

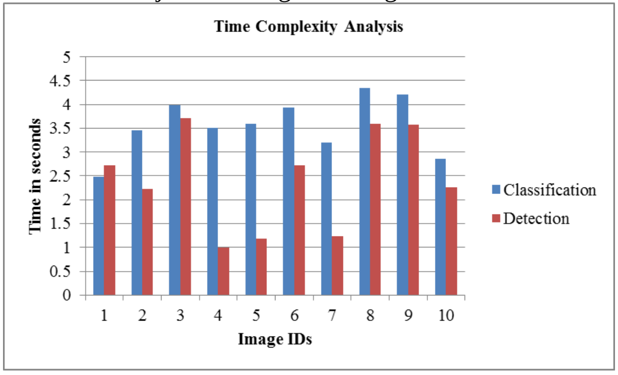

Fig. 1: The average time complexity analysis of ten images

The proposed model has been evaluated for its performance against the prominent existing models to estimate the performance enhancement. The proposed model results clearly indicate the improvement in the performance for the vehicular classification over the input image data.

Technique	Recall Value
HOG+SVM [19]	67.5
DNN [2]	23.5
Adaboost [21]	91.6
LBP+SVM [20]	87.6
Proposed	97.25

Table 3: The comparative analysis of the proposed model

V. CONCLUSION

The proposed model is based upon the visual similarity evaluation using the supervised appearance similarity model for the vehicular detection. The vehicular classification has been evaluated using the deep neural network for the purpose of classification of the vehicular objects in the form of heavy and light vehicular objects. The proposed model utilizes the non-negative matrix factorization (NMF) for the quick response classification system. The proposed model has undergone the detailed performance evaluation in the terms of various performance parameters, which are obtained on the basis of various statistical parameters. The performance evaluation results clearly indicate the improved performance in the terms of recall, which directly signifies the accuracy based upon the false negative values. The proposed model has achieve the maximum recall value at 97.25%, which is far better than 91.6%, 87.6%, 23.5% and 67.5% for the Adaboost, LBP+SVM, DNN and HOG+SVM respectively.

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