Research Paper Scheduling on Route Planning during Moving Road Networks

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Abstract— Vehicle recognition is an imperative stage in an intelligent automatic traffic control systems. Presently, vehicles outward appearance is a most important part of transportation. Moreover the utilization of vehicles has been growing in view of population growth and the rising human being needs in topical years. Organize of vehicles is turning into a main issue and significantly more hard to determine. Automatic vehicle recognition systems are utilized for the effective control of vehicles plying on roads. Automatic vehicle recognition (AVR) is a form of automatic vehicle identification technology. It is a technology used in image processing which is used to identify and detect vehicles only by their license plates. Real time AVR plays a very important role in monitoring the traffic system and takes huge care in ramam vehicle carries a single license plate, no external cards, labels or transmitters need to be recognized, only license plate. In the existing model, the complex background based on concomitant colors method has been realized for the vehicle detection in the multi-lane system. The existing model has been designed to work on the basis of the uneven clarification for the purpose of multiple vehicle detection on the multiple vehicles captured in the single frame. The existing model has been designed to work in the multiple rounds classify and compute the density of the vehicles over the vehicular object extracted by the various mathematical and morphological operations to extract the vehicle in the video frame data. The proposed model is aimed at using the neural network application for the classification of the vehicles detected in the frames in the input video data. The proposed model is aimed at solving the issue of accuracy in the vehicular object recognition and the vehicular object classification. The proposed model has undergone various experiments over the variety of the video supervision data for the performance assessment. The proposed model results have been found professional enough and better than the existing models by almost 15-25% on each parameter evaluated.

I. INTRODUCTION

Vehicle Detection can be characterized as distinguishing the vehicles on the basis of different parameters, for example, shading, shape and size .It can also be characterized as a system that executes the vehicle tracking. This is used to monitor traffic on roads [10]. The traffic flow on the roads can be measured by the fixed installed sensors like induction loops, bridge sensors and stationary cameras. The main part of the information about the urban road networks monitoring is represented by the movement of traffic on the smaller roads .Information about the on-road parked vehicles is not collected [1]. Vehicle detection can likewise be characterized as the identification of single vehicles by extricating the vehicle lines from the satellite imagery. The satellite imagery can be characterized as a snapshot of time i.e. it covers a generally incomprehensible region. The estimation is robust and repeatable after some time despite the fact that it can't be considered for ceaseless monitoring. The use of Satellite imagery is to evaluate the vehicle fleets in different countries and for these there is not an established ground based monitoring systems for traffic. Pre-processing is the basic requirement in the detection and enumeration of vehicles from satellite images [16]. Very high resolution satellite sensors provide images with different atmospheric conditions and with distinct viewing angles that can be influenced by the illumination and contamination conditions in the urban ranges. The spectral characteristics can also change by analyzing the multi temporal images [7].

II. LITERATURE SURVEY

Jazayeri et al. [1] propounded the detection and tracking of the vehicles in car for the purpose of safety, auto driving and target tracing. It is based on the motion information.

Broggi et al. [2] proposed a pedestrian detection system in order to increase the safety and to avoid collisions with vulnerable road users. This system defines the localization of dangerous situations under urban scenarios. It searches for the pedestrians only in the critical areas.

Premebida et al. [4] characterized the recognition and grouping of street clients that portrays an issue on security frameworks for shrewd vehicles drive. It depicts the investigation of passerby discovery by utilizing the laser based components as a part of urban ranges. The principle goal is to investigate the required data that can be separated from LIDAR sensors.

Song et al. [6] described a system for vehicles that is based on sensor network. SVATS is used to detect the unauthorized movement of the vehicle and tracking the vehicle that has been stolen. Since the rate of theft of vehicle is high, so alarm systems or tracking systems have been defined. Such systems have disadvantage like high cost and high false alarm rate. This is a very large system for tracking of the vehicles.

Arrospide et al. [8] described an approach for detecting the vehicles visually by using a gradient-based descriptor. This characterizes the characterization execution of symmetry in a Bayesian choice structure.

Unzueta et al. [9] proposed a robust vision- based system used for tracking and classification of vehicles for traffic flow surveillance. A robust adaptive multi-cue segmentation method is defined to detect the foreground pixels. This framework edge the mix of luminance and chromaticity uniqueness maps.

Sivaraman et al. [13] proposed a novel approach for localization of vehicles and tracking of vehicles that combines stereo- vision to the monocular vehicle detection. This system obtains the information from stereo- vision for 3D localization and also obtains monocular frames that are synchronized and hence calculate the depth maps.

Zhou et al. [14] defined about the extraction of features and for road detection, classification is done. For the road detection, an approach i.e. Support Vector Machines (SVM) is used which is an effective approach for self-supervised online learning.

Bota et al. [15] proposed a method for detecting, tracking and classification of the object that is based on stereovision. In this, the objects are detected by using points grouping algorithm or a density map grouping algorithm.

Nedevschi et al. [16] defined a real time pedestrian detection system that is useful for detecting the pedestrians in urban scenarios.

Cao et al. [18] described a method in order to detect the moving vehicles in urban traffic surveillance. The algorithms used must be efficient so that they can be used in a real time environment

Mei et al. [19] described a robust visual tracking method by using sparse representation. The sparsely can be achieved by solving a 1- regularized least-squares problem. The candidate with smallest projection error is taken as tracking target.

III. PROBLEM FORMULATION

In the existing solutions, the neural network has been used for the vehicle detection in the high and low-bit rate CCTV videos. The authors have used the neural network as a form of neural network has been used to evaluate the targeted objects from the high resolution satellite images. Neural Networks is a falsely keen bio-propelled calculation which can be utilized for the component extraction as portrayed in the base paper. Neural system is a type of feed forward neural system where the individual neurons are to be tiled in such a manner those they react to overlapping areas inside the visual field. Neural networks were energized by organic procedures and they really are the varieties that happen in multilayer perceptrons which are intended to utilize ostensible measures of pre-processing. They are for the most part utilized models for picture and video acknowledgment, being an impact apparatus for various vision related issues The basic problem of the existing scheme is this that the existing scheme is capable of vehicle detection only. The existing scheme does not perform any classification on the obtained vehicle data. The vehicle data can be classified on the basis of various parameters, such as vehicle type, colour, shape or size. The base scheme in the existing scheme is consisting of the convolution neural network. The convolution neural network is a category of feed- forward deep neural networks. The convolution neural network has been used for vehicle detection in the satellite videos, which can be used for various vehicle detection applications. The vehicle detection applications from satellite images can be used to count the density of vehicles in the cities, particular areas or other significant places, in order to obtain the data for preparing the traffic policies. Also such vehicle detection techniques can be enhanced for various vehicle tracking, classification or other applications. The basic problem of the existing scheme is this that the existing scheme is capable of vehicle detection only. The existing scheme does not perform any classification on the obtained vehicle data. The vehicle data can be classified on the basis of various parameters, such as vehicle type, colour, shape or size. The proposed technique will utilize a blend of the non-negative matrix factorization and Hybrid deep Convolution Neural Systems for the components extraction and locating the vehicles for the vehicle identification. The propounded system would be designed to perform better than the bare neural network in the existing or subsisting algorithm for the purpose of vehicle detection. The NMF will perform the image reconstruction and representation, which will improve the quality of the image. The proposed strategy will include the vehicle ordering on the premise of different parameters and properties or vehicles such as shading, sort, shape or size. The planned system would be designed to perform better than the simple HDCNN within the existing algorithmic rule for the purpose of vehicle detection. The proposed model uses the mixture of Non-Negative Matrix factorization (NMF) and Hybrid Deep Convolution Neural Network (HDCNN) The NMF can perform the image reconstruction and illustration, which is able to improve the standard of the image. The planned technique can embody the vehicle classification on the idea of assorted parameters and properties or vehicles like colour, type, form or size. .Additionally the proposed algorithm would be capable of performing the classification of the detected vehicles in an image. Both of the techniques, existing and proposed would be developed in this research project. The comparison of the both of the techniques, HDCNN and NMF-HDCNN for vehicle detection, would be performed at large using various performance parameters like Similarity, F1-measure, FRR, FAR, Precision, Recall, NPV, PPV, etc.

IV. OBJECTIVES

- To correctly analyze the vehicles in the videos.
- To correctly classify the vehicles using the knowledge based detection using the neural network.
- To develop the traffic analysis and reporting based upon the early vehicle classification.
- To produce the region wise vehicle classification report.

V. METHODOLOGY

At the first step, the literature review will be conducted on the concerned neural network techniques for the vehicle detection and image reconstruction. The techniques will be shortlisted for the creation of the hybrid model for the vehicle detection based on the neural network techniques. The problem formulation would be formed after finding the research gaps in the existing vehicle detection models. The proposed model would be framed and finalized using the repeated rounds of algorithm improvement and theoretical debugging. The proposed and existing models would be implemented in the MATLAB simulator and the results would be collected in the form of various performance parameters. The collected results would be analyzed in-depth and the conclusion would be prepared to project the final results of the proposed model.

VI. PROPOSED SYSTEM

The proposed technique will utilize a blend of the non-negative matrix factorization and Hybrid deep Convolution Neural Systems for the components extraction and locating the vehicles for the vehicle identification. The propounded system would be designed to perform better than the bare neural network in the existing or subsisting algorithm for the purpose of vehicle detection. The NMF will perform the image reconstruction and representation, which will improve the quality of the image. The proposed strategy will include the vehicle ordering on the premise of different parameters and properties or vehicles such as shading, sort, shape or size. The planned system would be designed to perform better than the simple HDCNN within the existing algorithmic rule for the purpose of vehicle detection. The proposed model uses the mixture of Non-Negative Matrix factorization (NMF) and Hybrid Deep Convolution Neural Network (HDCNN) The NMF can perform the image reconstruction and illustration, which is able to improve the standard of the image. The planned technique can embody the vehicle classification on the idea of assorted parameters and properties or vehicles like colour, type, form or size. .Additionally the proposed algorithm would be capable of performing the classification of the detected vehicles in an image. Both of the techniques, existing and proposed would be developed in this research project. The comparison of the both of the techniques, HDCNN and NMF-HDCNN for vehicle detection, would be performed at large using various performance parameters like Similarity, F1-measure, FRR, FAR, Precision, Recall, NPV, PPV, etc.

VII. RESULTS AND DISCUSSIONS

The performance parameters are the specified entities which defines the result of the implemented model. The performance parameters have to be selected on the basis of the nature of the project, algorithms being used and the testing data. The proposed model is based upon the vehicle detection and classification, which always requires the high accuracy in order to use it in the real time applications. Hence, the accuracy becomes the major parameter, which is being calculated in the various ways using the statistics. The proposed model accuracy can be measured in the terms of precision, recall and accuracy. The possibility of the false results also becomes important in the case of performance evaluation. Hence, the parameter selection also includes the results concerned with the appearance of the false results. The parameters of false rejection rate (FRR) and false acceptance rate (FAR) has been selected as the parameters to measure the possibility. Precision can be defined as the ratio of relevant retrieved documents and the information required by the users. High precision ensures that the algorithm returns results that are relevant as compared to irrelevant results. High precision also defines a predictive value that is positive and this is defined in terms of the binary classification. This classification describes the documents that are retrieved. It is defined in terms of the results that are returned by the system at some cut-off rank. Precision can also be called as sensitivity.

Precision = TP/ (TP+FP)

Where, A = True Positive
B = True Negative
C = False Negative
D = False Positive

Recall

Recall is the probability that a test will indicate or show 'test' among those with the matching sample.

Recall = A/ (A+C) * 100

Positive Predictive Value

Positive predictive values are affected by the prevalence of correct results in the population that is being tested. If we perform a test in a high prevalence setting, there is more probability that the people who test positive truly have matching probability than if the test is done on a population having low prevalence.

Positive Predictive Value = A/(A+B) × 100

Accuracy

The percentage of the result success out of the whole results is known as accuracy. Accuracy is also known as success rate.

Accuracy = (Correct Results/ Total Results) *100

False Acceptance Rate (FAR)

It is defined as the fraction of the system that do not match the input patterns accurately to the template that is non matching. It defines the percentage of inputs that are not valid. False acceptance rate is dependent on the threshold. It is also defined as the measure that an attempt by the user that is unauthorized will be accepted by the biometric security system.

False Rejection Rate (FRR)

The False rejection rate can be defined as the probability of a system to detect the matching between the pattern that is given as input and the matching template. It is the fraction of number of false rejections to the number of attempts that are identified. It defines a measure that an attempt by the user that is unauthorized is rejected by the biometric security system.

Result Analysis

The results of the proposed model have been obtained after performing the several experiments over the input video and image data obtained from the datasets containing the videos of traffic on the roads and squares. The proposed model results have been obtained in the form of recall, precision and accuracy of the vehicular object detection in the target objects. The proposed model has been designed for the mobility tracking among the video data obtained from the road traffic surveillance cameras. The following section clearly describes the performance of the proposed model over the video data specifically. The performance parameters are the specified entities which defines the result of the implemented model. The performance parameters have to be selected on the basis of the nature of the project, algorithms being used and the testing data. The proposed model is based upon the vehicle detection and classification, which always requires the high accuracy in order to use it in the real time applications. Hence, the accuracy becomes the major parameter, which is being calculated in the various ways using the statistics. The proposed model accuracy can be measured in the terms of precision, recall and accuracy. The possibility of the false results also becomes important in the case of performance evaluation. Hence, the parameter selection also includes the results concerned with the appearance of the false results. The parameters of false rejection rate (FRR) and false acceptance rate (FAR) has been selected as the parameters to measure the possibility

Precision

The parameter of the precision as computed in Table7.1 is one the parameters to calculate the accuracy of the system, which is entirely based upon the percentage of the total or aggregate matches found from the input data according the user requirement. The higher precision value signifies the robustness of the proposed model applied over the video data. The manual classification has been performed to measure the statistical type I and type II errors, which defines the overall results in the various categories or selection or rejection. The precision is also termed as the sensitivity and given by the following equation:

P = Alpha / (Alpha + Lambda) * 100

Where P is the precision, Alpha here stands for the true positive and beta stands for false negative.

Table 7.1: Evaluation of the proposed model using precision

PARAMETER	VALUE	95% CI
Precision	94.08%	75.29% to 100.00%

Recall

Recall as computed in Table 7.2, gives the overall probability of the test among the matching samples out of the total selected and rejected cases. The false rejection cases significantly reduces the overall accuracy of the system, hence the impact of the false rejection cases is studied with the parameter of recall.

Recall = Alpha / (Alpha + Gamma) * 100

Table7. 2: Recall based evaluation of the proposed model

PARAMETER	VALUE	95% CI
Recall	93.10%	75.29% to 100.00%

Positive Predictive Value

Positive predictive values are influenced by the prevalence of correct results in the population that is being tested. If we perform a test in a high prevalence setting, it is more likely that persons who test positive truly have matching probability than if the test is performed in a population with low prevalence.

Positive Predictive Value = A/(A+B) × 100

Table7. 3: Positive predictive value calculated from the simulation results

PARAMETER	VALUE	95% CI
Positive Predictive Value	93.50%	75.29% to 100.00%

Accuracy

The overall accuracy of the system as computed in Table7.4 is measure by dividing the correct number of the detection samples (True positive and true negative) by the total number of the test cases. The accuracy clears the overall performance of the system unlike the specific cases defined by the precision or recall. The following table defines the accuracy of the system:

Accuracy = (Total correct results/ Total test cases) *100

Table 7.4: Accuracy based evaluation of the proposed model.

PARAMETER	VALUE	95% CI
Accuracy	93.41%	75% to 100%

VIII. CONCLUSION AND FUTURE WORK

Conclusion

The proposed model has been designed for the vehicle object detection and classification from the video and image data for traffic surveillance of the urban areas. The proposed model has been designed using the deep neural network with the colour and appearance based feature extraction model for the purpose of object detection. The proposed vehicle detection and classification model has been designed to solve the problem of urban traffic monitoring, traffic and other studies or tasks such as traffic shaping, traffic management during the wee hours. The proposed model has been tested over the video and image data obtained from the various standard datasets or urban traffic surveillance camera. The image under the observation in the proposed model is the image clicked over the Oxford Square, London during the day time with the help of geo-stationary very high resolution surveillance camera during the day. The proposed model has been tested to classify the heavy vehicles and light vehicles in the given images. The testing image contains moving vehicular objects, out of which the five are the heavy vehicles (buses) and eight are the lightweight vehicles (cars). The proposed model has been designed in the multi-layered model for the detection and classification of the vehicular objects in the frames extracted from the videos. The proposed model results have been recorded on the basis of elapsed time for the vehicle recognition and vehicle detection transactions performed in the proposed model. The average classification time has been found around 1.2 seconds in the all of the given transactions to recognize the type of the 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 experimental 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 and efficiency 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.

Future Scope

In the future, the proposed model can be extended for the classification of the vehicles in the more number of categories such as heavy vehicles, super heavy vehicles, light vehicles, light heavy vehicles, etc. Also the time constraint can be improved by using the feature reduction scheme over the proposed model features, such as principle component analysis (PCA), independent component analysis (ICA), etc along with the robust classification algorithm such as back probabilistic neural network (PNN), deep neural network (DNN), support vector machine (SVM), random forest, Co forest, etc. The proposed model can be also extended by using the multi-level hierarchical classification using the heuristic or meta-heuristic classification algorithm, either in the combination or individually.

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