REAL-TIME OPTIMIZATION OF TRAFFIC SIGNALING TIME USING CNN

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Abstract

Transportation is one of the major elements of developing urban areas. In urban areas, traffic congestion problem occurs due to an increase in traffic volume. Traffic volume is dynamically changing in intersections and not consistent in all legs for all-day. But traffic signals are given by fixed time or manually by traffic signal operators. For the dynamic change in traffic volume, fixed time traffic signals lead to increasing traffic congestion problems in intersections. This problem can be reduced by designing an efficient traffic signaling time in intersections. In this proposed work, a model is developed by using conventional algorithms for designing the traffic signaling time and distributing the green signaling time based on real-time traffic volume present in the legs of the intersection. The real-time traffic volume is generated from the surveillance cameras by applying machine learning, and Convolution Neural Network (CNN) techniques. CNN algorithms are classified the vehicles with an accuracy of 62.92 percent in mixed traffic condition when compared to the results of Traffic Data Extractor (TDE) software, and the signaling time is optimized for each leg of the intersection based on the traffic volume present in the legs.

Keywords: Convolution neural network, machine learning, surveillance video, traffic signal time, traffic volume

Introduction

Traffic volume is rapidly increasing nowadays due to an increase in population, urbanization, industrialization, etc. and it leads to accidents, bottleneck, and also traffic congestion problems in intersections. Efficient traffic signaling control methods will reduce the traffic congestion problems and increase the free flow of traffic in intersections (Xu *et al*., 2019). In India, mixed traffic conditions are present on roads. Fixed Time Control and Actuated Time Control methods are not giving good results in intersections due to mixed traffic conditions and dynamic changing of traffic volume (Sadoun, 2003; Akoum, 2017; Zheng *et al*., 2018). Dynamic change in traffic volume and constant signaling time leads to traffic congestion problems in maximum traffic volume carried legs and losing of signaling time in low traffic volume carried legs. Adaptive Traffic Control System (ATCS) is useful for designing the traffic signal time based on real-time traffic volume and the data collecting through automatic counting devices like sensors, mobiles, cameras, RFID, etc (Zheng *et al*., 2013; Yao *et al*., 2020). In this work, data is collected by surveillance cameras which are already fixed by the police department for monitoring the intersections. However, these cameras will not provide the traffic

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volume data directly, so need to detect, identify and classify the vehicles from videos by applying image processing techniques like image matching, image recognition, and image classification, etc. (Ma *et al*., 2017; Senthilkumar *et al*., 2017; Lee and Park, 2018). But surveillance cameras generated a huge volume of data that is unable to process with traditional software and tools for real time optimization (Lee and Park, 2018). Big Data platform is useful for handling large and complex datasets like video data. Here, a model for traffic signaling time is designed in the Big Data platform using conventional algorithms for reducing the traffic congestion problems, queue length of vehicles and increasing the free flow of traffic on the intersection and publishing the data in Amazon Web Services (AWS) to display the traffic signal time to the users.

Introduction to Techniques Used:

CNN

CNN algorithms are useful for extracting the time and space dimensions of a transportation network and traffic density to predict the network speed and volume from an image or video (Ma *et al.*, 2017 ; Redmon and Farhadi, 2018).

Big Data

Hadoop is an open-source framework of Big Data platform for storing and processing massive datasets. In which storing the data is carried by Hadoop Distributed File System (HDFS) and MapReduce processes stored data.

Amazon Web Services (AWS)

AWS is a comprehensive and broadly adopted cloud platform. AWS is useful to publish the work or code or matter using S3 services.

The main objective of the study is optimization of traffic signaling time by the real time traffic volume which can be collected by classification of different types of vehicles from video data. From the classified data, counting the traffic volume for an interval of one second and designing the traffic signaling time and green time according to the actual traffic volume present in the legs of the intersection using Webster's method and conventional algorithms.

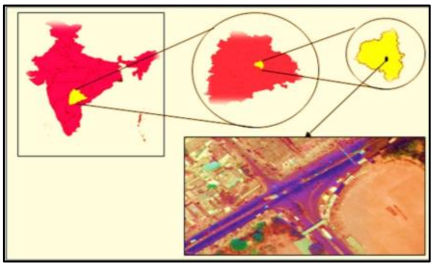


Figure1. Location of the study area in India

Study Area

Warangal is an urban area, selected as one of the smart city by the government of India and which is located in Telangana state, India (i.e. shown in Figure 1). The population growth is rapidly increasing in this location. In Warangal, various types of vehicles like Two-wheelers (16%), Autos and cars (29%), Cycles (10%), Walk (30%), Buses (11%), others (4%) are moving on the road. In this proposed work, signaling time is optimized in one of the intersection in Warangal area which is Kazipet junction. Kazipet junction is one of the highly traffic-congested area and the maximum traffic covered in the intersection by Auto Rickshaw, cars, and bikes.

Kazipet junction is a 4 - leg signalized intersection that is connected to two major roads (L_1 and L_3), which are carrying maximum traffic in the intersection and two minor roads (L_2 and L_4).

Leg – 1 (L_1) = Hyderabad to Hanamakonda road
Leg – 2 (L_2) = Kazipet junction to police station road
Leg – 3 (L_3) = Hanamakonda to Hyderabad road
Leg – 4 (L_4) = Kazipet junction to Railway station road

In this intersection, traffic signals are given by fixed time controlling method and the traffic volume is dynamically changing with respect to time.

Methodology

The methodology of the proposed work is shown in Figure 2, and it is describing the extraction and handling of the video data by applying CNN

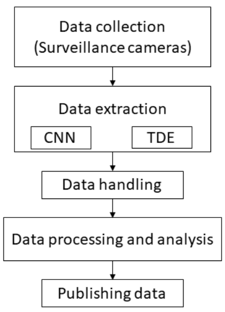


Figure 2. Flowchart for designing of a traffic signal in the Big Data platform

algorithms and image processing techniques using Big Data platforms to optimizing the traffic signaling time.

Data Collection

From the proposed study area, data is collected from four sides of the intersection by the surveillance cameras, which are already fixed. The data is collected for a span of one week from morning 7 AM to evening 6 PM. From each camera, approximately 3GB per one-hour volume is generated and it is an unstructured data format (mp4), and the camera builds 20 frames (images) per second. Surveillance images of Kazipet intersection are showed as Figure 3.

Data Extraction

For designing the efficient traffic signaling time, extract the traffic volume for every second, but the video contains a number of frames per a single second. In the proposed work, data is extracted by using TDE software and CNN algorithm.

Traffic Data Extractor:

IIT Bombay designed the TDE software for counting the traffic volume manually by the input of videos. Counting of the traffic volume is done by manual pressing of unique codes of each type of vehicle which are assigned by the software while vehicle passing through the Region of Interest (ROI) line and the counted traffic volume is extracted in the format of Excel or CSV. Figure 4 representing the extraction of traffic data from TDE software.

Extraction of Traffic Data from Convolution Neural Network:

In the proposed work, CNN algorithms are developed for classifying the vehicles from the sequence of images (video data) using image processing and machine learning techniques. CNN architecture (Figure 5) describing the procedure of classification of vehicles from the video data. From the video data, the OpenCV library extracting the single frame and divided into the 50 convolution layers. These convolution layers resolves the vanishing problems in trained traditional multi-layer neural networks by using back propagation and the output of the convolution layer sending as an input of the pooling layer. Pooling layers reduce the dimensions of the data by combining the output of neuron clusters at one layer to another neuron in the next layer. Fully connected layers connect to every neuron in one layer to every neuron in another layer. The flattened matrix goes through a fully connected layer to classify the images using the Common Objects in Context (COCO) dataset. Divide each region into its corresponding class and combine all these regions to get the original image with the detected objects along with the probability of classification of vehicles and continuing the process until the last frame of the video.

The detected vehicles and their probability

Figure 3. Surveillance camera images of all sides of the Kazipet intersection

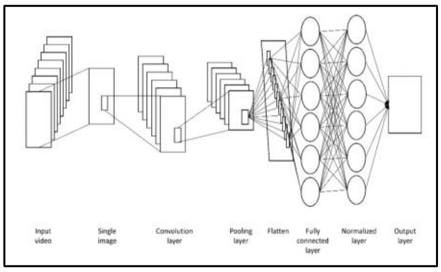


Figure 5. CNN Architecture

Figure 4. Data extraction from Traffic Data Extractor software

Figure 6. Detected vehicles in video data

values of the classified vehicle data are showed in Figure 6. After classifying the data, the probability(P) value of the selected vehicle in the video is assigned to each class and it is categorized into particular class based on the probability confidence(P(c)) of the vehicle developed an algorithm for counting each class of vehicle for each second and exporting the data into a structured data format like shown below.

P =	P(c)	C	Bike	Auto	Car	LCV	HCV

The above five classes are considered for the design of traffic signaling time, and the traffic volume count (C) is calculated by the probability of corresponding class (P(c)) of the vehicle. In that, vans and buses are considered under Low Commercial Vehicles (LCV) and heavy loaded vehicles are considered under Higher Commercial Vehicles (HCV).

Data Handling

The video data has to be stored in the different racks of the Hadoop framework for soft computing purpose. Hadoop framework is running in the Cloudera's Distribution Including Apache Hadoop (CDH5.13) platform. Name Node and Data Node are storing, handling and processing the data by applying the conventional algorithms based on the tasks performed on the video data and the resources (RAM, Graphics data) available. The output (structured data format) of the video data is stored in CDH 5.13 platform and that may process by traditional algorithms from the Webster's method for optimizing the traffic signaling time.

Data Processing and Analysis

For designing the traffic signaling time, convert the extracted different vehicular traffic count to Passenger Car Unit (PCU) value. The conversion values of vehicular traffic to PCU are shown in Table 1 and the conversion equation of traffic count to traffic volume in PCU is showed in Equation 1.

PCU of a particular second (Pi)
= ∑ (Type of vehicle * PCU factor (1)

Webster's method is a one of the methods for calculating the optimum cycle length and it is a critical approach for determining the optimum cycle length (Co) corresponding to minimum delay to all the vehicles at the approach roads of the intersection. The Equation 2 for optimum cycle length is shown below:

$$Co = \frac{1.5L+5}{1-Y} \tag{2}$$

where,
L = Total lost time per cycle in seconds = 2n+R = 18 sec
n = number of phases = 4
R = all-red time or red-amber time = 10 sec
Y = $y_1+y_2+y_3+y_4$
y_1 = q_1/s_1
Similarly, y_2, y_3, y_4
q = normal flow from each leg in veh/h = ∑Pi* 3,600/ C_0
s = Saturation flow changes based on the width of the road as per IRC and the flow values are showed Table 2.
w = width of the road in meters
Width of leg 1 and 3 = 5.5 m and
Width of leg 2 and 4 = 7.5 m

After calculation of signal cycle length, distributing the green time according to the traffic volume present on the road by using the Equation 3:

$$G_1 = y_1/Y\ (Co-L) \tag{3}$$

Similarly, G_2, G_3, G_4
G_1, G_2, G_3, G_4 = Green time of leg 1, 2, 3, 4.

Mapper and Reducer python scripts used in the Hadoop framework for designing the traffic signaling time by using Webster's method.

Publishing the Data

After processing the data, publishing the green signal time, pedestrian time, red time, and cycle length in Amazon Web Services using Google API for sharing the information to the users. The following link is useful for observing the traffic signal time variations in mobiles, iPad, etc., and the

Table 1. Recommended PCU factors for various types of vehicles in urban roads (IRC)

S. No	Vehicle type	PCU
1	Motor Vehicles	0.5
2	Passenger Car, Pick-up Van or Auto-rickshaw	1.0
3	Truck or Bus or Low commercial vehicles	3.0
4	Heavy commercial vehicles	4.5

Table 2. Saturation flow values according to road width as per IRC recommendations

Width (m)	3.0	3.5	4.0	4.5	5.0	5.5	> 5.5
saturation flow (veh/h)	1,850	1,890	1,950	2,250	2,250	2,990	525* w

interface of the published link shown in Figure 7. Published link: https://trafficsignallingdesign.s3.amazonaws.com/code.html

Results

CNN algorithms are extracted five classes of vehicles from the video and the data is exported into excel format like as shown in Table 3. Accuracy of the extracted traffic vehicular data is comparing with the TDE software results. In the TDE software, counting of vehicles is done by manually. Validation between the results of TDE software and vehicle object detection using CNN are compared for a period of 20 min (9.00 AM to 9:20 AM) data of Hyderabad to Hanmakonda (L4) leg and it is showed in Table 4. The extracted traffic vehicle count using CNN algorithms is matching with an accuracy of 62.92 percent compared to the TDE software results.

Traffic count data helps identify traffic flow patterns, trends, traffic volumes, capacity, identifying peak hours and designing traffic speed, etc. For identifying the peak hour volume, counting the data for each 15 min, and it is converting to hourly volume in terms of veh/h. Figure 8, represents the peak traffic volume that occurred in the morning time at 10:45 AM and evening time at 05:45 PM on 21_PCU (21-Jan 2019 (Monday)).

Initially, when designing the traffic signal time, counted the traffic volume for the first 120 sec. From the traffic volume of the first 120 sec, cycle lengths and green time are calculated. For designing the second cycle, counted the traffic volume from 121st sec to (120 + previous cycle length), the same procedure is continuously running till the last record. Table 5 represents the information of variation between calculated and optimized traffic cycle length at the time of 09:00:00 AM. From Table 5(a), at the time of 09:07:59 AM, the calculated green time of leg - 1 and 3 are 5 and 6 sec due to less traffic volume presence. But, as per IRC recommendations, the minimum green time of each leg is 9 sec. So, the green time is restricted to 9 sec and again calculated the next cycle length from the corrected previous cycle length. The corrected traffic signal time variation of each cycle is represented in Table 5(b). Distribution of calculated and corrected effective green time of traffic signal from 09:00:00 AM presented in Figures 9(a) and 9(b) and the green, red and amber signaling time variation of each leg is presented in Figures 10(a) and 10(b). Due to the optimization of traffic signaling time, the traffic volume distribution to each cycle is varied and the variations of traffic volume of before and after optimization are showed in Table 6 and it is also indicating that the increase in number of traffic signaling cycles and reducing the waiting period of the vehicles.

The calculated effective green time of peak hour time (10:32 AM) shown in Figure 11. From Figure 11(a), the cycle length (effective green time + all red time) at 10:38:39AM is more than 4 min. It leads to an increase in the waiting period of the vehicle in the intersection. For that, restricting the maximum cycle length to 4 min and corrected the traffic signal time according to the maximum cycle

Table 3. Counting of each class of vehicle for every second from algorithms

Time	Bike	Auto	Car	Low Axle	High Axle
9:00:00	0	0	0	0	0
9:00:01	1	0	0	0	0
9:00:02	1	0	0	0	0

Table 4. Validation between TDE output data and Vehicle detection data using CNN for a period of 20 min

Class of vehicle / Method	Object detection	TDE	Accuracy
Bike	142	249	57.03
Auto Rickshaw	45	117	38.46
Car	82	67	122.39
Low Axle	9	10	90.00
High Axle	2	2	100.00
Total	280	445	62.92

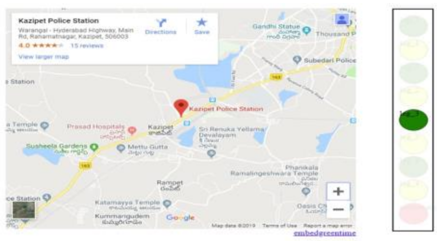


Figure 7. Published data in Amazon Web Services

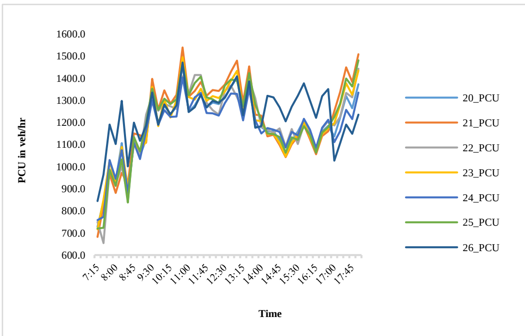


Figure 8. PCU vs. Time graph for leg - 4 for the period of 7 days (20 to 26 - Jan - 2019)

Table 5. Comparison of calculated and corrected traffic signal time from 9:00:00 AM

(a). Calculated traffic signal time(sec)

Time	leg - 1	leg - 2	leg - 3	leg - 4	C_0
9:00:00	12	14	21	20	85
9:01:25	13	19	23	12	85
9:02:50	10	17	12	12	69
9:03:59	13	16	24	26	97
9:05:36	11	64	24	26	143
9:07:59	5	23	6	10	62
9:09:01	9	48	10	16	101

(b). Corrected traffic signal time(sec)

Time	leg - 1	leg - 2	leg - 3	leg - 4	C_0
9:00:00	12	14	21	20	85
9:01:25	13	19	23	12	85
9:02:50	10	17	12	12	69
9:03:59	13	16	24	26	97
9:05:36	11	64	24	26	143
9:07:59	9	23	9	10	69
9:09:08	9	44	9	15	95

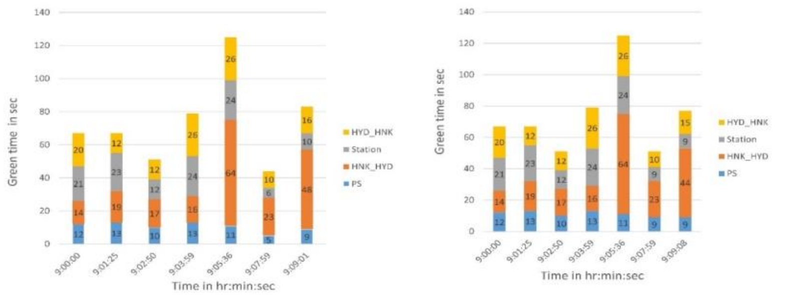
Table 6. Comparison of traffic volume (PCU/h) inflow to the intersection before and after optimization of traffic signaling time at 09:00:00 AM

(a). Before optimization

Time	leg - 1	leg - 2	leg - 3	leg - 4
9:00:00	334	513	584	733
9:02:40	620	1311	942	865
9:05:20	524	1996	1022	1467
9:08:00	345	1140	382	520
9:10:40	365	2113	370	813

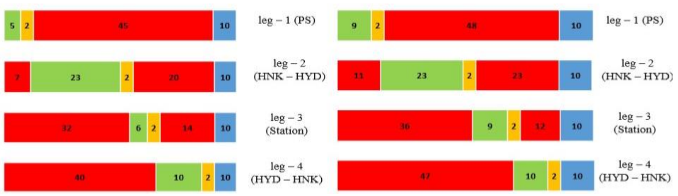
(b). After optimization

Time	leg - 1	leg - 2	leg - 3	leg - 4
9:00:00	334	513	584	733
9:01:25	362	696	640	440
9:02:50	314	704	377	497
9:03:59	330	534	609	868
9:05:36	204	1565	446	636
9:07:59	283	952	283	414
9:09:08	232	1492	232	509



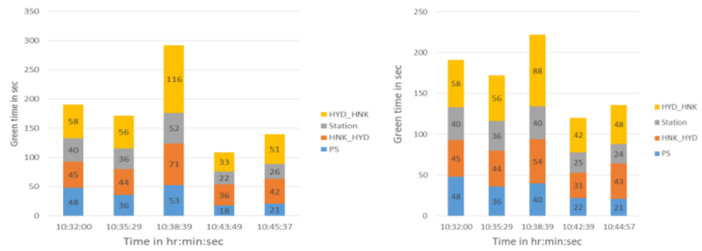
(a) Calculated effective green signal time (b) Corrected effective green signal time

Figure 9. Comparison of effective green time of calculated and corrected traffic signal from 9:00:00 AM



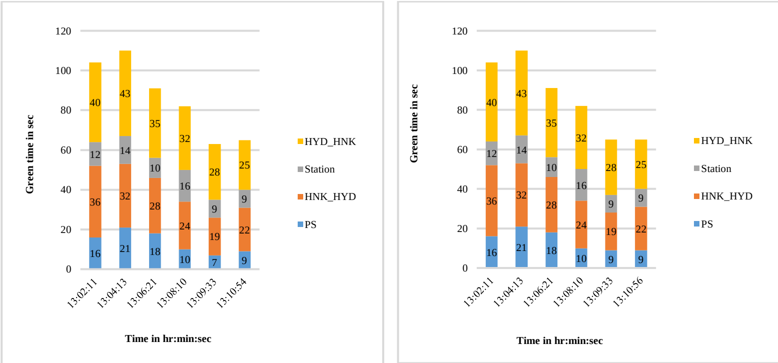
(a) Calculated signal timee (b) Corrected signal time

Figure 10. Comparison of the distribution of calculated and corrected traffic cycle length (sec) of all legs



(a) Calculated effective green signal time (b) Corrected effective green signal time

Figure 11. Comparison of effective green time of calculated and corrected traffic signal at 10:32:00 AM



(a) Calculated effective green signal time (b) Corrected effective green signal time

Figure 12. Comparison of Effective green time of calculated and corrected traffic signal from 1:01:11 PM

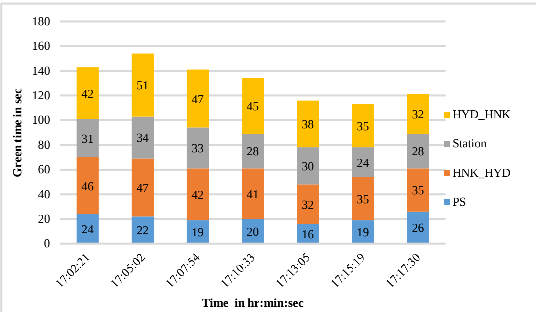


Figure 13. Comparison of effective green time of the calculated traffic signal from 5:02:21 PM

length. The corrected traffic signal time showed in Figure 11(b). Similarly, effective green times of calculated and corrected cycle lengths at afternoon sessions (13:02:11) are presented in Figure 12. The calculated effective green times of traffic signal time in the evening time (5:02:21 PM) are presented in Figure 13.

Discussion

From the results, the accuracy of the vehicular count from object detection is 62.92 percent and that is good sign in mixed traffic conditions. Observed from Table 4, 57.03 percent of bikes and 38.46 percent of auto rickshaws are only detected accurately and some of the auto rickshaws are detected under cars. In mixed traffic condition, all vehicles are moving in irregular manner, position of cameras is sometimes unable to see and detect the bikes and autos which are in another side of HCV. Probability to increasing the accuracy of object detection can be achieved by training the vehicle images in to detect the objects and installing the camera position in between intersection and connected roads. For classifying the objects accurately, train the data with large datasets before the performance of object detection.

From the results, traffic cycle lengths, traffic signaling time, and green time change from cycle to cycle by the corresponding traffic volume present in the intersection. But in the fixed time control method, traffic signal time is wasted in low traffic volume carried legs and that may be optimized to another leg of the intersection. In peak hours, the calculated cycle length is more than the maximum cycle length (as per IRC). But the cycle length is restricted to maximum cycle length due to this assigned traffic volume is completely not leaving the intersection on a particular cycle and that traffic volume is assigned to the next cycle. Based on the previous cycle length and corrected traffic volume, alternative cycle lengths are calculated. In the early morning time and afternoon time, very less traffic volume is coming to an intersection and the assigned cycle length and green time is also less. So the queue length and waiting time in the intersection is going to be decreasing.

Conclusions

From the above discussion, the proposed CNN algorithm gave good results for extracting the traffic volume. It can be improved by increasing the accuracy of the training dataset and changing camera angle for seeing all vehicles. From the extracted traffic volume, traffic signaling time is optimized, and the traffic signaling time for each leg is distributed based on actual traffic volume presented in the leg of the intersection. The developed model is suitable for 4 legged intersections and also it can be modified to ant type of intersection.

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