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AI-Based Congestion-Aware Traffic Light Using Open CV

Ankit Kumar, Utkarsh Raj, Vartika Jain, Shivank Dubey, Pranav Kumar
Computer Science& Engineering, RKGIT, Ghaziabad, UP, India

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Abstract
The rapidincreaseinurbantrafficcongestionis attributed largely to the rising number of vehicles and the high variability in traffic demand at road intersections. The majority of the existing traffic signals still follow the fixed time plans and thus, cannot adjust to the real time traffic conditions effectively. This situation often causes delays, increase in the consumption of fuel, and higher emissions.
In this paper, a density based intelligenttraffic signal control system is introduced, which integrates computer vision and machine learning to adjust the signal timings dynamically basedonrealtimevehicledensity. For identifying and counting the vehicles from the live camera feeds, a deep learning based object detection model is deployed, and the dividing regions of interest for each road approach have been defined. The green time allocation for lights is made according to the density of the traffic detected, giving priorityto the directions where the demand isgreater. Besides, the system has an emergency vehicle preemption mechanism that detects ambulances and instantly provides them with the right of way in order to minimize emergency response delays. A physical model of a four way intersection was created and testingwasdonewitharealtimesoftware pipeline and a scaled road model. The resultsof the experiments show that the proposed method can manage traffic signal times effectively during periods of varying traffic while still providing dependable support for emergency vehicles and the likes of ambulances prioritisation.
Keywords: Adaptive Traffic Signal Control, Traffic Density, Computer Vision, Deep Learning, Emergency Vehicle Pre emption

I. Introduction

Urbantrafficjamshavebecomeaconstantissue and are one of the major drawbacks of rapidly changing cities. Among the main factors that have contributed to this problem are the surge inthenumberofvehiclesandimbalancedtraffic distribution at road junctions. The conventional traffic light systems that are still widely used, signaled by lamps, mostly depend onfixedtime schedules where the green phases are predetermined, and vehicles waiting at the red light are not considered. Although easy to implement, fixed time control does not provide very good results when the traffic demand varies and, as a consequence, long queues of waiting cars are formed on thecongestedroads while the green light is on for almost empty streets. Such situations cause longer travel times, more fuel consumption, and higher greenhouse gas emissions.

The solution to these problems might lie in the adoption of a traffic management system that changes the signal in accordance with the presence of cars; hence the name adaptive traffic signalcontrolhasbeenapromisingfactor in the development ofintelligenttransportation systems (ITS). Adaptive systems typically work by altering the signal timingsinrealtime,based on the traffic information provided,whichleads to better intersection efficiency andasmoother traffic flow. Furthermore, recent research has suggested that applying the power of artificial intelligence, particularly deep reinforcement learning and hybrid adaptive methods, can reduce average delay and improve throughput significantly when compared to conventional fixed time control systems[1],[2].However,the reliance on extensive roadside sensor infrastructure for most of these approaches pushes installation and maintenance costs up and hence limits large scale deployment.
Monitoring the traffic via computer vision has proven to be a less expensive option,especially in cities where closed circuit television (CCTV) cameras are already there on a large scale. Vehicle detection under diverse traffic and lighting conditions has been greatly improvedby deep learning to the point that live camera feeds can yield [3], [4] reliable traffic density estimation. The YOLO family lightweight object detection models have overcome the impediments of real time traffic applications owing to their marked balance of speed and detection accuracy [5], [6]. The use of camera based vehicle counting instead of invasive sensors would open the door for the extremely cost effective deployment and distributed nature of adaptive traffic control systems.
An important feature of the old and most modern

traffic control systems isthemovingup of emergency vehicles. The time that ambulances spend waiting at intersections can havedireconsequencesforpublichealth.
Current research suggests that theincorporationofemergencyvehiclepreemption directly into adaptive signal control systems should come instead of treating it asaseparate function [7], [8]. The emergency vehicle prioritization must work in such a way that it allows quick passage for emergency vehiclesand at the same time keeps disruption to normal traffic at the lowest level.
This paper, guided by these reasons, puts forward a density based intelligent traffic signal controlsystemthatunitescomputervision–based vehicle detection with adaptive signaltimingandemergencyvehicle pre-emption.Thesystemusesdeep learning–based objectdetectiontoestimatethe real time traffic density and dynamically allocates green times based on demand while providing immediate priority to ambulances upon their detection.

II. Literature Review

Adaptive traffic signal control based on AI is usually investigated using DRL, in which signal actions are acquired to reduce the waitingtime or to increase the flow of vehicles under different demands [2], [4]. The reviews written in 2024 to 2025 mention the improvements made in the areas of state representation, reward design, and multi agent coordination; however, they mention such practical problems as transferability, safety constraints, and deployment complexity [2], [4], [11]. At the same time, monitoring usingcamerascalculates the density of traffic by spotting and tracing vehicles and subsequently linking the counts to thetimingdecisions.Thesystemsarethoughtof as being appealing as they have comparatively low installation costs and are compatible with the existing surveillance infrastructure [3], [12].

Deep learning detectors from the YOLO family and lightweight models are the most common methodsusedfortrafficscenesduetotheir speed and accuracy balance, allowing almost real time inference [6], [7]. Accurate vehicle detection is still a primary requirement for correct density estimation and controlling operations that follow [6] [8]. The prioritisation of emergency vehicles has gained considerable attention. The recent methods envision the emergency vehicle being provided with a green phase and include reversing queue spillback, coordination at the route level, and minimisation of disruptions [5], [9], [10]. Such findings lead to the idea of integrating emergency detection into an adaptive signal framework instead of treating it as a separate.

System Design and Prototype Description The suggested framework monitors traffic atan intersection using a camera positioned overthe approaches. Every single image is analyzed to identify cars, and to calculate the number of vehicles for each direction in predetermined regions of interestROIs.Thelogicforcontrolling traffic lights grants longer green periods according to the current demand of the direction with the highest number of cars but within the limits of minimum and maximum green times decided for the sake of safety and stability. The moment an ambulance is spotted, the traffic light controller switches into an emergency mode giving the ambulance direction an instant priority that is in line with emergency pre-emption goals outlined in the literature [5], [9], [10].

The physical model consists of a four way tiny junction, LED signal heads, and a circuit board for controlling the signal lamps wired to the lamps. The first photograph of the project depicts the entire junction layout with the mounted signal unit that has different colored LEDs for red, yellow, and green phases inFig.1. The second picture depicts adifferenttrafficset up with an ambulance toycarplacedtotestthe emergency logic in Fig. 2). Two more screenshotsillustratetheoutputsofrealtime detection including boxes drawn around the vehicles, their class labels, and current vehicle count in Figs. 3 to 4.

Fig.1.PhysicalprototypeintersectionwithLED trafficsignalsandcontrollermountedonpole

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Fig. 2. Prototype traffic layout including an ambulance vehicle for emergency priority testing

Fig. 3. Real time detection output showing five detected cars and computed vehicle count

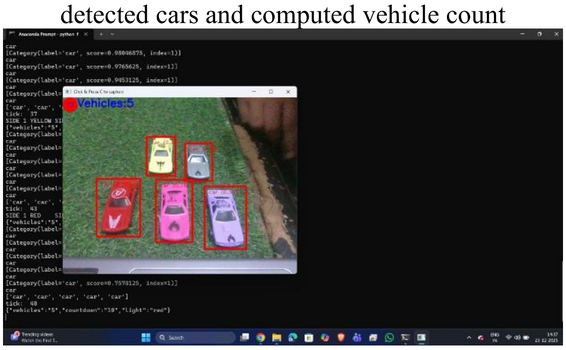

Fig. 4. Real time detection output showing ambulance detectionandupdatedvehiclecount under emergency scenario

III. Methodology

VehicleDetectionandCounting

A deep learningobjectdetectorisusedtoresize and process every incoming frame. The objects detected are filtered according to the class labels thatareimportantforroadtraffic(forthis prototype: car and ambulance, and then assigned to a lane/approach according to the ROI the centre of the bounding box falls into. This method of counting based on ROIs is quite common in the field of monitoring traffic as it yields stable counts without the need of full multi object tracking in short time windows[3], [12].Usually,lightweightdetectionnetworksare favoredfortheirrealtimeperformanceand they have been proved to be effective for vehicle detections in traffic scenes [6], [7].

DensitytoTimingMapping

The controller makes adecisionregardinggreen time allocation based on the count of vehicles. Instead of relying on a fixedplan,itrecalculates the green splits at every decision point. The mapping is kept simple and understandable for the purpose of showcasing and at the sametime reflecting the principle of giving more service to higher demand, which is in line with the adaptive signal control objectives [3], [4]. Minimum green time is applied to avoid oscillations and switching is confinedtotheend of a decision interval.

EmergencyPre emption

The system activates emergencymodeoncethe detector detects an ambulance in any of the approach ROIs. The controller in emergency mode promptly gives the green light to the ambulance approach (or keeps/extends the green light if it is already active) and at thesame time stops the conflicting movements. This isinlinewithrecentstudiesthatemphasize the need for rapid emergency passage and still take into accounttheeffectsonothertraffic[5], [9], [10]. In this prototype, the priority is on accuracy and speed; future developments can add to the system route level strategies or queue spillback constraints as proposed by recent research [5].

IV. Result and Analysis

The prototype provides evidencethatthesignal timing is altered according to the density detected. In the regular situation, where five vehicles were present at one approach, the system indicated “Vehicles: 5” and the controller grantedalongergreenperiodforthat movement (see Fig. 3). After that, when the ambulance was added, the sensor recognized the “ambulance” category and the controller optedforemergencyprioritymode,changing

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the signal state and countdown simultaneously (see Fig. 4).Thiskindofbehavioralignswiththe primary purposeofminimizingemergencydelay while allowing adaptive control for other directions to continue [5], [9], [10].

The timing policy applied in this case is summarized in Table I. The policy determines the green time by referringtocountthresholds. The settingofthethresholdsportraystheactual notion of density responsive green splits prevailing in several adaptive schemes, while at the same time ensuring the logic remains transparent for evaluation and demonstration purposes [3], [12].

Table I. Density based green time policyusedin the prototype

Density level (by count in ROI)	Vehicle count	Allocatedgreen time (seconds)
Low	0–2	10
Medium	3–4	15
High	≥5	20
Emergency override	Ambulance detected	Immediate/priori ty green (pre emption)

Table II presents detection confidence intervals observed during the testing and visible in the console output. Although this is not acomplete benchmark assessment, it demonstrates that the detector made high confidence detectionsin the controlled prototype environment. Previous studies suggest that modern detectors can achieve significant vehicle detection performance while being efficient for real time monitoring at the same time [6], [7].

Table II. Observed detector confidence ranges during prototype testing

Detected class	Typical confidence range (observed)	Practical note
Car	~0.75–0.99	Stable detectionfor multiple vehicles (Fig. 3)
Ambulance	~0.85–0.99	Triggered emergency override reliably (Fig. 4)

In general, theoutcomesbackuptheviabilityof the intersection control through camera based adaptive control. The resultsareinlinewiththe extensive literature that indicates the usability of AI powered adaptive control in having faster responsescomparedtofixedtimesystems [2]–[4].

V. Discussion

Responsiveness is the main advantage of this technique: the signalfollowsthedemandthatis being measured instead of relying on average conditions. This, in turn, minimizes the risk of very long queues forming on a heavily loaded path when green time could be used in other places. The emergency logic incorporates operational value because fast passage is demanded by emergencyvehicles,andrecently, the literature has pointed out that pre-emption should be very well planned since it hasnegative effects on normal traffic [5], [9], [10].

The authors recognize a number of restrictions. Initially, detection may not be as accurate in poor lighting, occlusion or very severe weather. Secondly, counting depends on the area selected for counting vehicles; if the area for counting is notproperlyset,itwillleadtoeither undercounting or overcounting of the vehicles. Furthermore, every real deployment needs to deal with issues of privacy, calibration, and robustness of the system. These difficulties are in line with the practical issues that were pointed out in the recent ITS surveys and adaptive control reviews [2], [4], [12]. Notwithstanding these limitations, the prototype shows a credible path for low cost deployments where cameras are already in use.

VI. Conclusion

The paper introduced a method for controlling traffic signals based on the density of vehicles detected through deep learning counting and ROI based counting which dynamicallyallocates the signal timer. Afunctionalprototypeandreal time detection outputs reassured that the method alters the signal's duration in accordance with varying traffic density and the doctors can be allowed through emergencypre-emption. Urbanareaswillfindtheapproach to be quite suitable due to its dependency on camera input instead of extensive sensor networks. Next steps should involve testing the approach under live junction camera coverage, connecting multiple camera spots, andassessing learning based timing optimization including DRL, improving scalability and performance, in line with the recent research directions in AI driven traffic signal control.

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