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Adaptive Headlamps in Automobile: A Review on the Models, Detection Techniques, and Mathematical Models

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ABSTRACT Driving at night with traditional headlamps poses significant threats, with many accidents occurring during the night because of temporary blindness caused by the headlights of the oncoming traffic. When in high beam, the headlights cause temporary visual impairment of human eyes called the Troxler effect. While it reduces the time to react, it also leads to decreased visibility which contributes to most mishaps that occur at night. Customarily the headlight adjustments are controlled manually where poor driving skills or error in judgment can have catastrophic effects. Accidents also occur due to poor lighting conditions as the current regular headlamp configurations do not illuminate the roads precisely, especially during curves and on unpredictable terrains. Hence, there is a need for adaptive headlamps in automobiles that can prevent Troxler's effect on the drivers of the opposite vehicles while not compromising the road's illumination for the driver on-board. This paper reviews research papers and patents to understand various methodologies used in implementing adaptive headlamps and explore the scope for future work in this area of research. This paper also reviews vehicle detection algorithms and various vehicle mathematical models for headlamp control based on steering angles.

INDEX TERMS Adaptive frontlight systems (AFS), adaptive headlamps, geometric path tracking, headlight sight distance, HOG, kinematics model, SIFT, SPP-NET, SURF, Troxler's effect, YOLO.

I. INTRODUCTION

Automotive Electronics has acquired a distinction as it does not just improve auto's comfort; it also helps ensure safety. Statistics show that accidents at night are more pronounced than those in the daytime, although the traffic volume during the night is fundamentally lower than the former [1], [2]. In India, nearly a third of crashes occur during the night when visibility is poor, and found the National Institute of Mental Health & Neuro Sciences [3]. These accidents may be attributed to lighting conditions on-road, lack of proper illumination by the headlamp, or even Troxler's effect. The headlamps in most of the vehicles today are controlled manually, with a large percentage of drivers switching not between high and low beam which often results in accidents when the illuminated light causes momentary blindness in the driver advancing in the opposite direction, or reflections from the mirrors in case if the other vehicle is ahead. This is called the Troxler's effect. The chances of havoc due to these are further pronounced if the pathway is a curve or uphill. Also, the typical low beam frameworks do not brighten the correct way on bent roads, resulting in an increased number of accidents involving pedestrians [4]. Hence, it becomes predominantly essential to have an advanced framework that could effectively switch between high and low beams and effectively illuminate the pathway. The point is to enhance perceivability for drivers, thus accomplish a noteworthy increment in security and driving experience by lighting the street ahead in the night at the corner. The review aims to determine the scope for developing products to prevent accidents at night due to high beams and hence contribute to society by saving lives and developing technological solutions that is less expensive and affordable. The paper outlines the developments in the intelligent headlamps in section II and reviews various approaches in object detection and tracking in section III and the mathematical models

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of vehicles for headlamp control based on steering angle in section IV.

II. ADAPTIVE FRONTLIGHT SYSTEMS IN VEHICLES

An automatic front light systems framework ensures better visibility to drivers by carrying the beam projections as the vehicle traverses [5]. As shown in Figure 1, using an AFS system, the beam lobes of the headlamp are varied according to the side where the vehicle takes a turn to improve the drivers' perceivability of the road and avoid accidents involving pedestrians or other objects. This framework is a simple system that controls the headlamp divergence using a stepper motor.

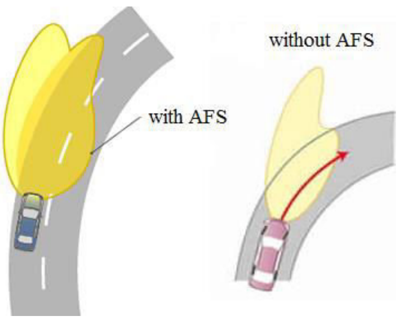


FIGURE 1. Beam projections in a vehicle with AFS and other without AFS system [5].

The team of Dahou *et al.* [5] further developed an AFS on FPGA Board using Pulse Width Modulation Technique and aimed at aiding both the onboard driver and the oncoming driver as the safety of the latter is as crucial as that of the former. The team designed a parabolic lighting system where four LED lamps coordinate to illuminate the road, as shown in Figure 2. An HB(L/R)- High Beam (Left/Right), and LB(L/R)- Low beam (Left/Right), LBM (Low beam Middle), and LB(R/L)- Low beam (Right/Left). The HB and LBM lamps are placed parallel to the roll axis, while LBL & LBR, in the case of the left headlamp, are placed at 10 degrees and 20 degrees to project the beam side lobes.

The combined trajectory of light beams projected from each of these lamps is changed based on the input from the steering wheel, and the zero state beam projection as shown in Figure 3 is obtained. The HB lamp projects high-intensity light on the trajectory path while the PWM Modulator controls the projection of the LB lamps by the ON/OFF method based on the vehicle motion. The PWM technique controls the frequency and the electric power given to the stepper motor and controls the electrical power applied to the lamps of the car's lighting parabola.

The PWM circuit adjusts the brightness of the low-beam lamps according to the type of state it receives. The work caters to most test cases with the bending angles in the range of 0 degrees to 45 degrees tested, and the results are found effective. However, the system's latency, i.e., the response time for the system to adjust to the changing driving condition, is to be discussed and is critical for an automobile

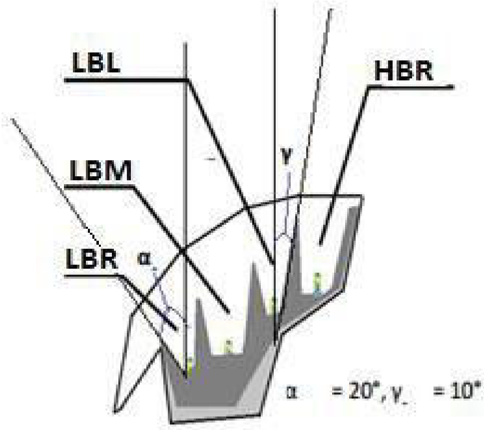


FIGURE 2. LED arrangement in the parabolic AFS design [5].

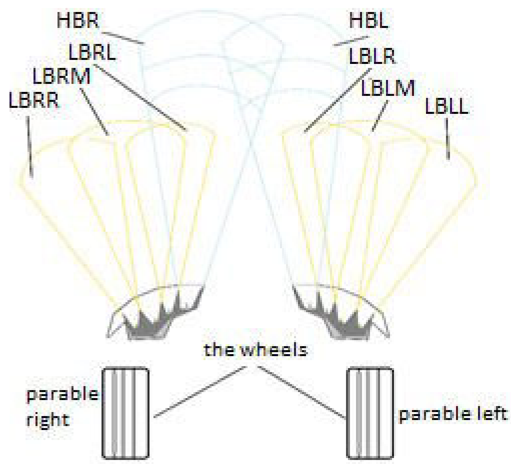


FIGURE 3. The combine trajectory in zero state [5].

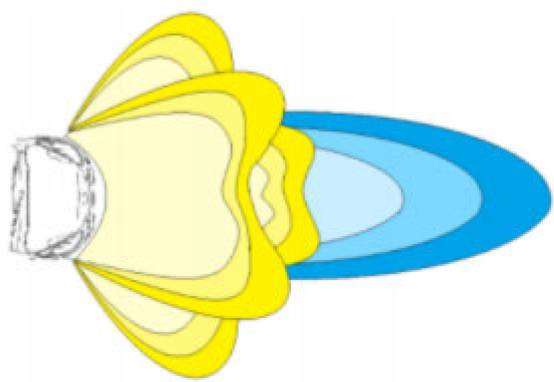


FIGURE 4. The parabolic headlamp illumination in zero state state [6].

application. While this system contributes to improving the onboard driver's visibility, it takes no measure to aid the driver in the on-coming vehicles, which is essential.

Cesar, D. S., & Castro, M. [6] developed headlamp swiveling algorithms based on the geometry of the highway to decide on the HSD(Headlight Sight Distance) its

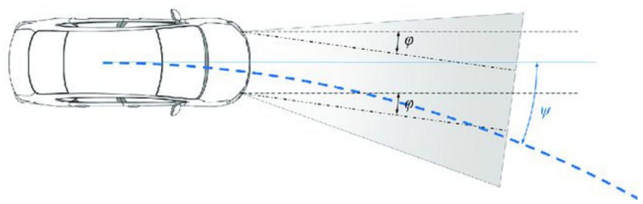


FIGURE 5. Swindeling headlamp concept of relative angle with respect to driver & headlamp [6].

performance was studied as shown in Figure 5. To assess the HSD, the headlamp beam is adjusted according to the headlamp position of the vehicle relative to that of the driver, and the geometric equation for the position of the headlamp was deduced.

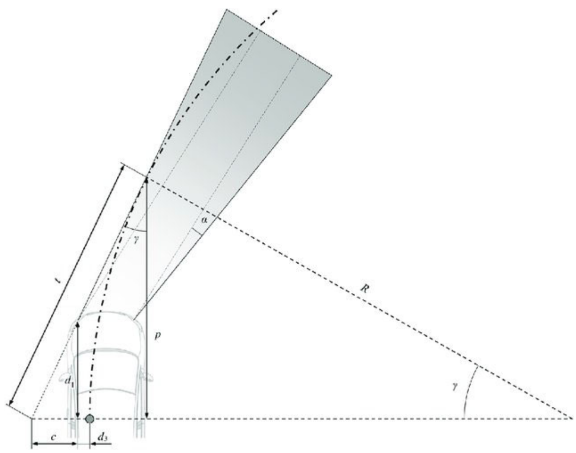


FIGURE 6. Arc projection used in the SGPSA algorithm [6].

Based on the mathematical equation derived from Figure 6, the Steering-Governed Predictive Swiveling Algorithm (SGPSA) HSD was developed and simulated on MATLAB for various test cases. The outcomes demonstrated that the swiveling headlights essentially increase sight distance. It tends to be presumed that the algorithm offers potential increments in HSD based on the steering angle.

The design of the arc is of great importance because they provide a proper transition between alignments of different curvatures from the standpoint of driving comfort, but they do not perform adequately enough in the event of sudden curvature changes ahead of the vehicle. Also, the system is not calibrated to meet the highway standard, which is crucial. Finally, in [6], system performance in varying speed conditions which is predominantly essential is not conducted.

The Hardware-in-loop vehicle model [7] uses a single-track non-linear model with a simple engine and produces for varying steering angle and throttle inputs, different yaw rate, and velocity. The model has a vehicle simulator and road model simulator that provides different input cases to the system and the Adaptive Headlamp System. The HIL model provides results that correlate well with the changing trajectory of the vehicle. The controller ascertains the necessary angles precisely for the actuators and the step

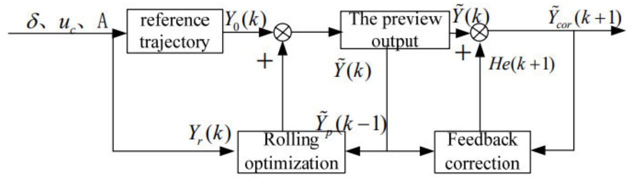


FIGURE 7. The closed loop preview control model [8].

motor controllers provide smooth passes of the front light angles instead of discrete or abrupt changes. Consequently, any uncontrolled behavior that could cause a frenzy response or disabling driving habits is forestalled. Additionally, any uncomfortable illumination for other drivers is avoided. The framework responds with different angles of the steering wheel input at varying speeds. While the model gives promising results, it needs to be tested extensively on a wide range of test cases, and the model needs optimization on size and power for real-time implementation.

The bending mode control was proposed based on preview control to address the issue with lag in the adaptive headlights [8]. In this approach, the mathematical relations governing the safe braking distance, steering: Wheel angle, and the vehicle's turn radius were deduced, and the simulation platform was developed as shown in Figure 7. The model is better in terms of the response time when compared to that with the traditional servo-controlled smart headlamps.

On comparing the response time of servo-controlled and Preview control model at a speed of 40 km/hr, the response time of the latter was found to be 0.4s faster than the former, and it also showed better response to change in driving angles. The prediction model has shown acceptable results at medium driving speeds. However, efficiency at higher speeds has to be further explored.

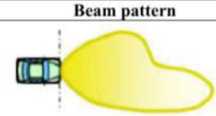
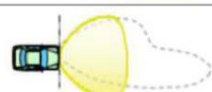
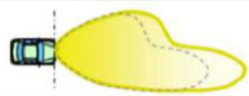
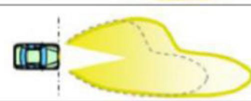
Class	Functions	Beam pattern
C	Basic or Country passing beam	
V	Urban passing	
E	Highway passing	
W	Wet-road passing	

FIGURE 8. The beam pattern produced by the system [10].

Lee *et al.* [9] designed an adaptive headlamp system to work automatically with the four classes of operation as defined by the United Nations Economic Commission for Europe regulation (ECE324-R123). The developed model has a quad mode which has a neutral state/ country light (Class C), urban light (Class V), highway light (Class E), and adverse weather light (Class W), as depicted in Figure 8.

Using the on/off of the LED array, the team designed the optics, which produces these modes through the cutoff and spread module, where the cutoff module lights the narrow central area with high intensity, and the widespread beam of low intensity through the spreading module. These two optics modules combine to form the four beam patterns using a simple on/off modulation of multi-array LEDs. The device switches to one of the four modes based on the vehicle's speed, exploiting the fact of the speed limit in each of these driving modes. However, speed cannot be the only feature to decide on the mode of driving. Hence an intelligent switching mode is predominantly essential. Also, manual shift to these modes would be cumbersome for the driver and would deter the actual need for this system.

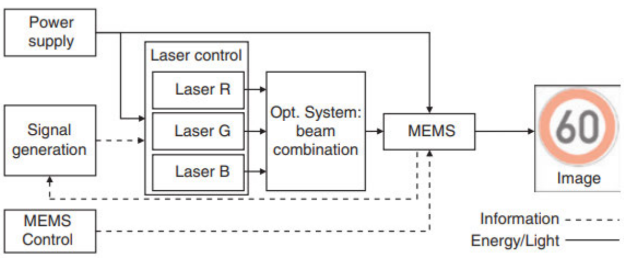


FIGURE 9. The beam pattern produced by the system [10].

A Laser-based approach was proposed by Kloppenburg *et al.* in [10] by mixing colored light of two diodes and combining three or more diodes, adaptable color symbol projection, and white light generation was possible using the setup shown in Figure 9. Quality color rendering is crucial for the proper illumination of the objects.

Also, the work involved generating a long wavelength UV or blue signal from a short wavelength using Phosphor. The emitted light of the blue diodes was mixed with converted yellow light to generate White light. The laser diodes emit a small band around the peak and hence are monochromatic.

This is suitable for projection, whereas for illumination it is the Color-rendering-index is essential to cater to the ECE regulations for which a minimum amount of red light (610 nm $\leq \lambda \leq$ 780 nm) is used with at least one of the diode emitting this required range, and the arrangement of the required arrangement angles was presented as shown in Table 1.

The work does significantly solve the problems associated with high beams, but generating a specific color of light using a combination of laser diodes does come with inherent challenges since they have to be precisely aligned, as shown in Figure 10. Since the lasers are used at a constant current, the output power rises above the threshold, below which the emission is negligible and above being linear.

It is the diode temperature that rules this threshold, and it is not easy to maintain the temperature in an automotive application. Hence generating the exact color adjustment using a specific color combination poses an immense challenge when implemented in real-time application.

TABLE 1. Diode characteristics in the scanning unit [10].

Diode Color	Red	Green	Blue
Optical output power	0.5W	0.15W	1.6W
Emission wavelength	638 ± 6nm	520 ± 10nm	450 ± 10nm
Beam divergence (I_{FMHW})	36	23	23
Beam divergence (II_{FMHW})	6	7	7
Polarization	p	s	p

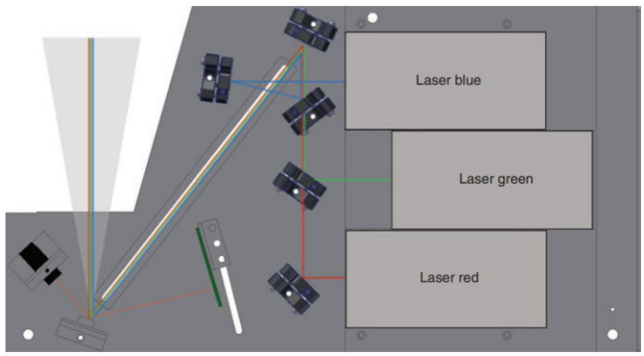


FIGURE 10. Optical scanning system setup [10].

A responsive visual framework was proposed in [11] with very low latency to detect, respond, and adjust rapidly to any climate while moving at speeds even as high as the highway limits. Anti-glare high beams, improved driver perceivability during low visibility, expanded differentiation of lanes, markings, sidewalks, and early visual warnings of deterrents are implemented. The framework works on a three-stage pipeline: Capture, Process, and Transfer. Capture hints at the camera exposure, while the Process involves image analysis and the transfer, the transfer of data between camera & computer and the computer to the headlamp adjustment control module.

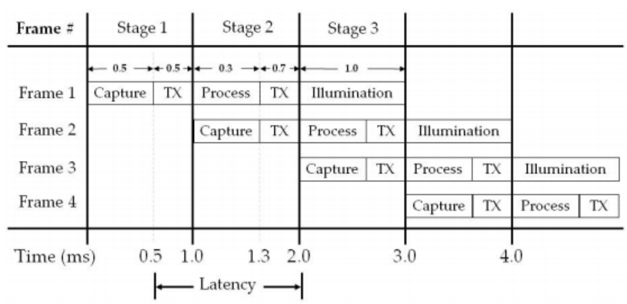


FIGURE 11. The timing diagram of the three stage adaptive system [11].

The architecture claims to have latency as low as 1ms, with 63% of times the reaction time being within the peak of two standard deviations, as shown in Figure 11. However,

FIGURE 12. The headlamp experimental setup on a vehicle [11].

the statistics are based on only six trials that need to be validated with ample numbers of trials, and it was tested in an experimental setup and not real-life cases that may differ from the projected results. The prototype, as shown in Figure 12, greatly needs optimization in terms of size and power.

For years, the automotive industry has been leading the development of adaptive headlamps for better illumination of the roads and improving the driving experience. A few industry leaders like Ford Corporations, Hella, and Nissan Corporations were at the forefront of this area. This section would discuss a few patents in this field of research.

FIGURE 13. Beam patterns for projections in the ford AFS [14].

A team from Ford Global Tech has developed an AFS with Dynamic LED headlights depicted in Figure 13, which has an electronic driving light framework with an illumination source, a projection lens, combined with a digital micro-mirror [13]–[15]. The lighting framework, which received a Mexico patent [12], additionally incorporates a camera. The controller is designed to decide on an objective parking spot and start the electronic adaptive driving light to outline its limit ceaselessly. A helpful night-driving guide, the Auto High Beam briefly dips the headlights when it identifies approaching traffic or a vehicle ahead, halting Troxler's effect on other drivers. Later, the system naturally returns to the

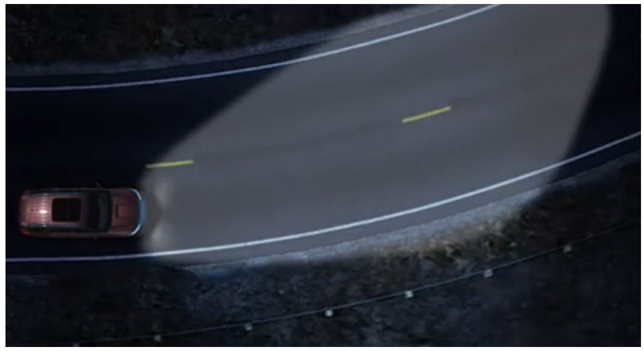


FIGURE 14. The beam projections across a curve in the ford AFS [14].

high beam, giving the greatest perceivability, as shown in Figure 14. Adaptive Lighting with Ford Dynamic LED headlights has LED arrangement that creates an exact light pattern, and their strongly characteristic light gives exceptional illumination.

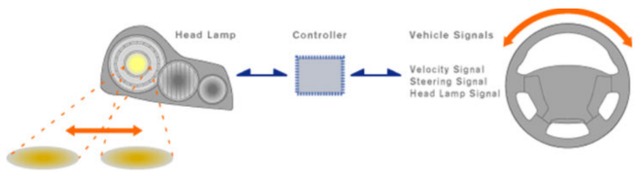


FIGURE 15. The nissan motor corporation AFS representation [16].

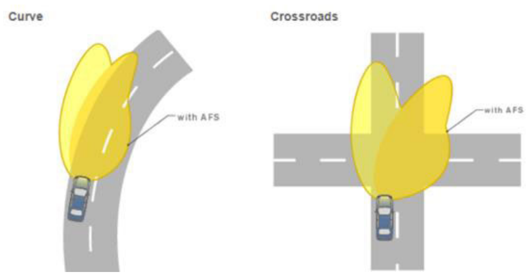


FIGURE 16. The nissan motor corporation AFS representation [16].

When driving over a bend, AFS will change the beam lobes to change the pattern of lighting to make up for the change in trajectory to help improve night perceivability, which received a European patent [16]. At road junctions, as shown in Figure 15, AFS will illuminate the direction to which the vehicle would take a turn and aid the driver immensely.

Teams from Nissan Global developed an AFS that naturally turns on low beam as per vehicle speed and steer to give better perceivability, as depicted in Figure 16.

In addition, companies like Hella, Valeo, Toyota Corporations, BMW, and Mercedes Benz have developed their company-specific models and have patented a few. A comparison of the pricing of a few adaptive headlamps is depicted in figure 17 [17]–[19]. Porsche Dynamic Light

System (PDLS), Chevrolet Intellibeam, Genesis Adaptive Cornering System (ACS), Mazda Adaptive LED Headlights (ALH), Ford Auto High-Beam Headlamps, Mercedes-Benz Intelligent Light System, Subaru: Steering Responsive Headlights, Lexus Adaptive Front Lighting System, Volkswagen Dynamic Cornering Light, and Lincoln Adaptive Pixel LED Lighting are the market competitors in the adaptive headlamps.

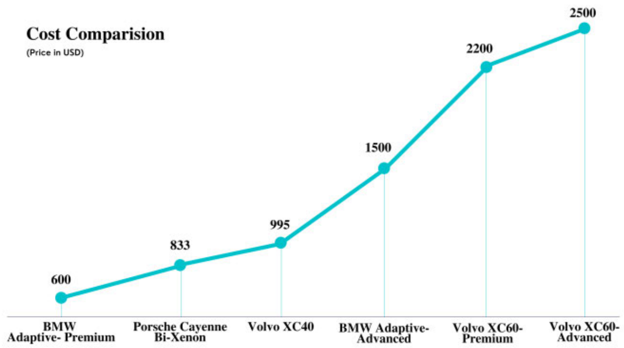


FIGURE 17. Prices of advanced headlamp system from various companies in US dollars [17]–[19].

As depicted in Figure 17, the cost of these products needs attention from researchers who must work on developing low-cost solutions. Say, an automotive market like India, where primarily mid-range cars are on the road the highest, adding a feature this expensive would be a challenge that many manufacturers would not take. The paper reviewed the works carried out in the design and development of adaptive headlamps, be it mechanical-based control systems, camera-based systems, and a few sensor-based systems modeled mathematically. Table 2 compares different systems in terms of their design, significant work, and the possibility of extended work.

III. VEHICLE DETECTION APPROACHES

The design of adaptive headlamps necessitates target detection and tracking to control the beam lobes effectively. The detection process identifies the object in the frame, and the tracking could be performed by repeatedly detecting the object in each frame. However, this is not preferred as it is a computational overhead in terms of speed and efficiency. Hence target tracking algorithms that use the data like size, shape, direction from the previous frame are used to anticipate the position in successive frames. This does not require a huge search in the frame, unlike the detection, hence improving response time. When target detection and tracking are performed simultaneously, the possibility of detection failure cannot be ruled out as it depends on the object features extensively. However, a tracking algorithm can still predict the next position based on speed and vehicle position from the previous frame. This section reviews various approaches used in object identification techniques suitable for the on-road applications as depicted in Figure 18 and classifiers for detection shown in Figure 19.

TABLE 2. Comparison of the different adaptive headlamp systems.

System	Methodology	Observations
Adaptive headlamps using PWM on FPGA [6]	Parabolic lamp design with four lamps in each headlamp that are placed strategically at certain angles to produce different beam lobes in response to the steering angle	• The work caters to test cases with bending angles in the range of 0 degrees to 45 degrees effectively. • Latency of the system, not discussed
Swiveling headlamps based highway geometric design [7]	MATLAB based Steering-Governed Predictive Swiveling Algorithm: Mathematical modeling	• Steering angle and swiveling headlamps positioning developed and are apt for the smooth curvy road • Response to sudden curvature changes to be addressed and Speed Vs performance study to be conducted
Hardware-In-Loop Simulation model [8]	The non-linear single track model and a simple engine provide the yaw rate and the velocity for different steering angles and throttle inputs. Hardware-in-loop Simulator creates a vehicle-road model as well as the adaptive headlamp system	• The angle of the headlights changes depending on the steering wheel input, vehicle speed, and vehicle's yaw rate in the lateral direction. • The controller calculates the required angles for the actuators in an accurate manner • Tested on limited road conditions and a generic model. Real-time response not attributed.
Preview control based bending mode control system [9]	The simulation model has deduced geometrical relations among safety braking distance, and the rate of steering-wheel angle & turning radius of the vehicle and a mathematical model is developed to control the illumination	• Response time at 40 Km/hr found to be faster by 0.4s when compared to servo-controlled systems • Found efficient at medium speeds, but the response in higher speed range needs to be evaluated
Adaptive headlamps for UN economic Commission Europe Regulation [10]	Quad Mode: Country, Urban, Highway, Wet road Uses Cut-off (for narrow central area) & Spread Module(for widespread)	• Shifts to one of these modes based on speed • Suitable for places with stringent speed regulation enforcement
Programmable adaptive Headlight [11]	The spatial light modulator uses a digital micro-mirror device that detects vehicles and objects to the beams using a beam splitter.	• Low Latency: 1-2.5 ms • Needs miniaturization • Compensation for effect due to vehicle vibration and heat to be provided

TABLE 2. *(Continued.)* **Comparison of the different adaptive headlamp systems.**

Optical scanning based high-resolution headlamps [12]	The MEMS system controls white light luminance by generating it through R,G, and B photodiodes, which are focussed using a lens that diverges the individual colors as needed.	• Needs more efficient diodes, and diode heating an issue • Performance at dawn or late evening not satisfactory
Ford Global Tech AFS with Dynamic LED headlights [13]	The electronic driving light framework has an illumination source, a projection lens, combined with a digital micro-mirror, and has a camera for object detection using image processing	• Correlations between lamp and wheel turn are found to be good. Identifies the object and beams less light on the objects to make an intensity variation and alert the driver. This reduced intensity also reduces Troxler's effect on the subject if the object is a living being • High processing capability makes it not viable for smaller vehicles. The cost factor also hinders its use in mid and range vehicles
Nissan Global AFS [16]	Beam adjustment according to steering angle and direction indicators and mathematical model is developed	• Turns on low beam as per vehicle speed and steer to give better perceivability • At road junctions, AFS will illuminate the direction to which the vehicle would take a turn and reduces accidents due to low illumination • Limited features of beam modification. No detection of oncoming traffic or adjustment

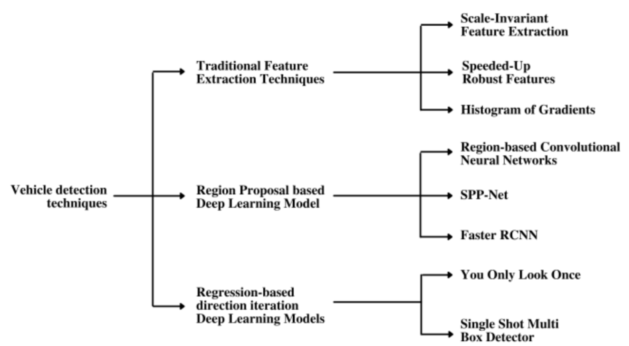


FIGURE 18. Classification of the techniques for vehicle and on-road object detection.

An object or vehicle detection technique involves defining the region of interest, extraction of features, and

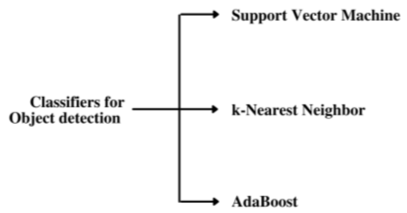


FIGURE 19. Classifiers used for object detection.

classification. The detection of vehicles through video can be through models based on appearance or motion [20]. While appearance model detection is based on the color, size, or shape, the latter works on relative object comparisons with the background. The former exploits prior knowledge to section the foreground from the background. The detection of vehicles can be performed through traditional feature extractors like SIFT [21], SURF [22], HOG [23] and classifiers like SVM, which are complex, time-consuming, or through deep learning region-based models like R-CNN, Fast R-CNN, or regression methods like YOLO, SSD. This section reviews methods of feature extraction, classifiers, and deep learning models for target detection.

Scale Invariant Feature Transform (SIFT) is an approach used extensively in detecting objects like cars or bikes from a video where recognition of the crucial features from a frame is through segmentation. The feature points defined in SIFT method show invariant to rotation of objects, changes in the image greyscale, scaling, or even the illumination conditions, making it ideal for object tracking in challenges where the object changes often in pose or illumination [20]. This works predominantly well for planar than 3D objects. Here the feature is compared with new images and the feature that matches well are found using Euclidean distance. Then based on the match features, the probability of the existence of an object is computed. Studies have shown that descriptors based on SIFT perform better compared to other contemporary descriptors and show robustness, high distinctiveness [21] since they are region-based and are conducive for matching features. A vital feature detector and descriptor in computer vision extensively used for recognition, registration, and Classification of the image are Speeded Up Robust Features(SURF) that uses integral images using the Hessian approximation, increasing the speed of detection remarkably compared to SIFT [22]. The choice of SURF or SIFT is problem-dependent and is majorly attributed to the speed parameter where SIFT is found to perform better in applications where the computational time can be compromised or is not critical [23] and also hints that Gaussian derivative-based SIFT descriptors are better than SURF descriptors.

Another feature descriptor used extensively for categorizing the objects is the Histogram of Gradients that deeds the gradients of the image or the edge orientation to define the features [24]. Here the normalization of parameters like gamma and color is performed in the small images derived from the larger frame to improve efficiency. The detector window explores the original image region-by-region to obtain the small image and scales it. Primarily, HOG deploys an SVM classifier. This descriptor has shown better performance than wavelets and has shown significantly closer performance to SIFT when gradient-based detection is performed using HOG and needs local-contrast-normalization significantly and cannot use a central-based scheme. The approach is distinct through its computational efficiency, even in deterring illumination conditions and object positioning.

While performing object detection, feature extraction is followed by Classification, where the class of the object in an image is envisioned, and there are distinct ways of implementing classifiers. When models are fed with features and the decisions are established around the decision boundary, it is referred to as unsupervised, and if the model processes the dataset exquisitely, then it is a supervised classifier. A supervised classifier that finds extensive application in object detection from video, aspect ratio, and color-based detection is a Support Vector Machine(SVM) [25]–[28].

The classifier finds a hyperplane that can distinguish between two classes amongst the fed dataset. SVM then finds the data points closest to this hyperplane called the support vectors and calculates their distance from the separating line called the margin. The larger the margin, the better is the classifier. SVM's are predominantly used for image classification and regression owing to their robustness to errors in the model, their efficiency, and the need for limited features for Classification. The increased efficiency is attributed to the quadratic programming problems used in their development and the data mapping to Hilbert space and suppressing errors by selecting appropriate trading values and insensitivity parameters [29]. The selection of a relevant kernel to characterize the dataset and the run time for the large dataset is a challenge.

K-Nearest Neighbor classifier is a simple non-parametric algorithm that performs classification based on the training sample positions with respect to their class [30], [31]. The effective distance between the dataset and the training sample is computed. The samples close to the threshold k value and the class with the most inbound samples (majority voting in the data record) are predicted to be the matching class. In multi-dimensional cases, Euclidean distance is measured. The classifier labels the objects, computes the metric of similarity or the distance and the k value for adequate classification. The classifier is ideal for classes that are multi-modal, and the error could be approximated and easily predicted as it is comparable to Bayes's error but poses a computational tradeoff as the dataset becomes larger. Generation of a robust classifier from a group of weaker classifiers is performed in the AdaBoost algorithm for object detection [32], [33]. Here the weaker classifiers are adjusted by the algorithm at the end of each learning cycle. While the ease of implementation distinct Adaboost from the other classifiers, it also exhibits faster concurrence and needs no knowledge of the weak classifiers' pre-existent state, and shows excellent performance.

The classifier models rely on time-consuming datasets training and hence ruled out for big datasets, which has led to the development and rampant use of Machine learning models, especially for object detection in videos. Algorithms like YOLO and SDD are regression single-stage models and use CNN to classify R-CNN, Fast R-CNN, SPP-Net, and Faster R-CNN are region-based two-stage processes where a target box is created first and classification later. Region-based Convolutional Neural Network (R-CNN) is an object detector that is region-based [34] with noticeable performance improvement when compared with traditional models discussed earlier. The multi-stage algorithm proposes at least 2000 multiple regions through a selective search for each image [35] and extracts features by cropping each proposed region, and creates a 4096-dimensional feature set that is highly robust. An SVM classifier predicts an object using this feature set. While the algorithm prerequisites the images to be of a fixed size, it may also lead to the generation of redundant proposals, and the feature extraction and the training are time-consuming. The need for having fixed image sizes which is a hindrance, is overcome using the Spatial Pyramid Pooling- Net(SPP-Net) [36]. It has a Spatial-Pyramid-Pool, which aids the generation of the feature vector with no need for uniform image sizing utilized by the SVM classifiers and the bounding-box regressors. The algorithm shows higher efficiency and shorter response time than R-CNN but is still time-consuming as it is a multi-stage process and depends on fully connected layers.

To improve the accuracy and also the operation speed, Fast R-CNN [36], [37] uses a detector that estimates the feature-length and determines the pooling region of interest (also used in SPP-Net) that predicts the fixed feature size that is fed to the fully connected classification and bounding-box which the CNN uses for improved classification. Fast R-CNN network layers are processed in a single stage and are faster because convolution is performed once per image while compared to the multiple proposed regions in R-CNN. Though better than the earlier discussed schemes, the algorithm remains slower due to the selective image search that it performs. To improve this stated problem, a Faster R-CNN [38] provides the convolution features of the complete image and avoids selective search for proposing the ROI through a distinct network. It uses a specialized layer called the Region Proposal Network(RPN) that can operate on images of different sizes and create the feature vector, which is fed to the classifier and the regression layer. Although the algorithm shows faster response, it does not show great response in images with paramount shapes or even scales.

Review of the region proposal-based algorithms does hint at the scarce possibility of their implementation in real-time, where time is the critical overhead, and hence regression models that are less time consuming are preferred. You Only Look Once [40] is the foremost one-stage model in this genre that looks only at the region with a high probability of having the object. Here, the image is divided into matrix cells, which is predetermined, and each of these cells is a proposal. The improved model of Yolo, V2, and V3 [40]–[42] shows improvement in accuracy and speed of detection and is used extensively for object detection in videos [43]–[46] though there are underlying issues of localization in this algorithm. YOLO is faster than the region-based models, but accuracy is not on par with the latter, especially in distinguishing objects of smaller size and images with different aspect ratios. The SSD algorithm [47], [48] strives to overcome the issues of YOLO architecture. It achieves speeds comparable with Faster R-CNN by performing region proposal and classification in a single stage. from the feature map, SSD probes the anchor boxes generated on different aspect ratios to output the bounding spaces. It also fuses the predictions obtained from different feature maps to deal with objects of various sizes. SSD does no filtering, unlike CNN algorithms, and performs faster detection compared to multi-stage algorithms with a compromise on accuracy. SSD uses non-max suppression to combine bounding boxes that are similar and effectively uses hard negative mining to club these boxes, often created on large numbers with no objects.

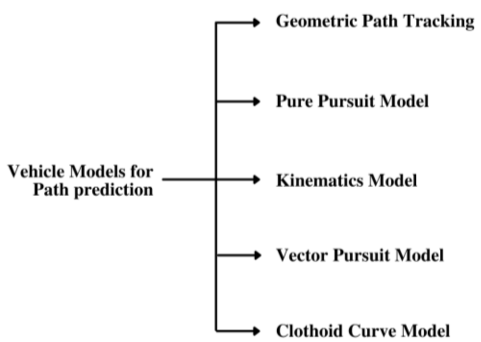


FIGURE 20. Major vehicle models used for path prediction.

IV. VEHICLE MODELS FOR ADAPTIVE HEADLAMPS

Along with detecting oncoming vehicles and tracking, it is predominantly essential to adjust the headlamps according to the road curve. This involves developing mathematical modeling of the vehicle, and this section discusses various vehicle models, as shown in Figure 20. Vehicle modeling using geometric path tracking is modeled using the vehicle position, its dimension, look ahead of the trajectory, and the orientation with no need for the parameters like velocity or other external features [49]. Nevertheless, this model inherently comes with the overhead of complexity in the algorithm for selecting the look-ahead-distance, which when at a larger distance escapes the corners of the path and directly ends at the new point and leads to the oscillation at high speeds. The Kinematic model exempts the need for considering internal/ external forces but advents to use the position and acceleration of the vehicle in relation to the coordinates (local and global). The absolute model using the bicycle model considers the front wheels that are steerable as the fixed coordinates with the front axle as the origin [50]–[53]. Various controllers were developed [54], [55] to make the model apt for linear and rotational motion with relatively better stability. The extended Kinematic model, unlike the former, also considers the tire slip, coupling [56], coefficient of friction [57].

The pure pursuit model [58] where along with the look ahead, the error between the goal of the direction in which the vehicle is heading is determined by defining a circular arc between the point at which the vehicle is at present with the final destination defined by the look ahead. This model was extensively reviewed [60]–[62] and has been found suitable for an array of applications [59], but its use for adaptive headlamp vehicle model design cannot be suggested due to its dependency on look-ahead distance. The vector pursuit exploits the coordinate system, which predicts the necessary orientation for arriving at the endpoint, which could be used in adaptive headlamps [63], but the computational overhead restricts its use. The Clothoid Curve method gets away with the arc and can operate in real-time and has improved and reliable performance [64].

Similarly, the dynamic path tracking method also uses the force acting due to ground and the tire contact, longitudinal and the lateral forces that act on the wheel [49], [65]. While the vehicle models show promising results, controllers to reduce error and cope with uncertainties are crucial. Adaptive controllers based on Kinematic and dynamic models [66]–[68], neural network [69], PID controller [70] shows high stability, performance even at varying conditions, but their development is intricate, convoluted, and complex. The Model Predictive Controllers tend to optimize the algorithms and hence reduce the cost overhead. The non-linear vehicle-based MPC [71], extended kinematic-based model [45] are the most prevalent models. Robust Controllers [57], [72], [73] though highly complex and robust in their design, can negate the unpredictable changes in dynamically changing conditions.

V. DISCUSSIONS

The need for adaptive headlamps to improve driving conditions and reduce the mishaps that occur at night due to high beams cannot be undermined. Table 2 compares different prototypes, products, and patents in the segment. The review finds that though immense work has been carried out and still in progress, these systems' performance at varying speeds is not stable, with most of these designed at a specific boundary constraint of speeds. These models are also not extensively tested at different driving road conditions, and their response time is crucial. Advanced models with better performance tend to add the computational overhead as the algorithms are complex and become expensive.

The review described and compared various approaches for object detection are summarized in Table 3. SIFT, SURF, HoG are the traditional approaches and are predominantly used for object detection. However, their use for object detection in high-speed vehicle driving conditions is ruled out since they require either good illumination or complex processing. Region-based deep learning model RCNN is time-consuming and creates redundancy, SPP-Net although

TABLE 3. Comparison of the approaches for object detection.

Category	Approach	Remarks
Traditional feature extraction model	Scale Invariant Feature Transform [20] [21]	• Suitable for detection in conditions with changing poses and illumination • More pronounced performance for planar objects than for 3D and better than contemporary descriptors. • Displays robustness and is a highly distinctive region-based feature extractor
	Speeded Up Robust Features [22] [23]	• Uses Hessian approximation of images • Apt for a system with quick response requirement
	Histogram of Gradients [24]	• Feature extraction is performed using gradients of the image or the edge orientation • Efficiency improvement through gamma and color normalization in the small images obtained from the larger frame • Better performance compared to Wavelet transforms and comparable performance with SIFT
Region proposal based deep learning Models	Region-based Convolutional Neural Network (2014) [34][35]	• Upto 2000 regions are generated from each image, and create a 4096-dimensional feature set is created • Fixed image size is required • Redundant proposals may be generated • Feature extraction and training costs time
	SPP-Net(2015) [36]	• Can operate on varied image sizes • Better efficiency but depends on fully connected layers hence time-consuming
	Faster RCNN (2015) [37-39]	• Estimates the feature-length and determines the pooling region of interest to predict the fixed feature size • Single-stage processing where the selective search is avoided to improve speed and uses Region Proposal Network instead for generating feature set • Improved accuracy and reduced operational speed compared to R-CNN • Response to change in shapes and scales needs improvement
Regression-based direction iteration deep learning Models	You Only Look Once(2016) [40-43]	• The image is divided into a predetermined number of cell matrices • Three versions available: Yolo, V2 and V3 with improved accuracy and detection speed • Apt for real-time object detection from videos • Faster response but accuracy not on par with region proposal based models, especially for detection of small objects and images of varied aspect ratio

TABLE 3. *(Continued.)* Comparison of the approaches for object detection.

Category	Approach	Remarks
	Single Shot MultiBox Detector(2016) [47][48]	• Speed of operation is similar to Faster R-CNN since region proposal and classification is performed in a single step, but accuracy of latter is more • Non-max suppression and hard-negative mining for combining redundant bounding boxes
Traditional Classifiers	Support vector Machine [25-29]	• The margin or distance of datapoint distance from Support Vector/ hyperplane is calculated. Hyperplane can be even multi-dimensional • Increased efficiency due to data mapping to Hilbert space and suppression of errors by selecting appropriate values of trading off and insensitivity parameters • Choice of a relevant kernel for a dataset and large run time for the huge dataset is a challenge
	K-Nearest Neighbor classifier [30][31]	• Non-parametric algorithm that computes the distance between the dataset and the training sample and those samples which are close to the k value and the most inbound class is used for match • Euclidean distance is used for multi-dimensional classification • Suitable for multi-modal classes and the error is comparable to Bayes error • Computational overhead is an issue as the dataset grows
	AdaBoost Algorithm [32][33]	• Uses weak classifiers to create strong classifiers • The weaker algorithms are updated after every learning cycle • Needs no prior knowledge of the preexisting(weak classes) and shows improved performance in terms of speed

efficient its dependency on layers costs time. Faster RCNN copes with this, but the performance in changing object shapes is not appreciable hence cannot be pronounced for adaptive headlamp systems where the vehicle moves at varying speeds and objects are unpredictable and subject to changes. Regression-based models, YOLO, and their versions show high performance and are apt for object detection in adaptive headlamps and could be exploited for this application.

Table 4 summarizes the different vehicle models to predict the vehicle movement and their feasibility for adaptive headlamps. The geometric model of the vehicle undermines the external factors and the vehicle speed and acceleration, which is a bottleneck for the models' implementation in real-time at varying speeds.

TABLE 4. Comparison of the different vehicle models to predict the path of travel.

Category	Approach	Remarks
Geometric path tracking [49]	• Uses vehicle position, dimension, and look ahead point data • Does not consider external perturbations	• Challenging when the distance to the endpoint is larger, which might lead to loss of corners
Kinematics [50]-[57]	• Exploits the position, velocity as well as acceleration of the vehicle with respect to the local and global coordinates • Does not consider external perturbations	• Complexity and increased computational time is an overhead.
Pure Pursuit Model [58]-[62]	• In addition to look ahead direction, error calculator using circular arc	• Not apt for adaptive headlamp vehicle model as the look-ahead direction is an overhead
Vector pursuit Model [63]	• Uses coordinate system for predicting the path	• Apt for adaptive headlamp design
Clothoid Curve Model [64]	• Uses Clothoid Curve instead of the Arc	• Efficient in real-time and could be used for adaptive applications • Complexity is high. Hence the cost and increased latency.

The Kinematic model progresses ahead with the inclusion of these features in the algorithm design but is highly complex. The extended model further improves by considering external perturbations, making the system more complex but feasible for real-time applications. Since the model uses these factors, the system becomes expensive as it necessitates the need for precise sensors.

VI. CONCLUSION AND FUTURE SCOPE

The review highlights the need for advanced headlamps for an automobile to ensure that driving is safer and more comfortable. Current research focus in this area is case-specific, and most of the solutions cater only to a few test cases and are not tailor-fit for varying speeds and road conditions. Firstly, the products in the market work well in countries where the lanes and lane markings are predictable and well defined, which is not the case worldwide, and the system needs to be intelligent to be accustomed to predict and control the headlamps without the dependency on lane markings or traffic signs. Universal implementation of these is still at an early phase as the functionalities are limited. The solutions to date are performing well in Urban limits and crossovers, whereas cases of sudden turns, multiple crossover lanes need to be addressed, and a significant region for future work.

Second, the correlation between speed and performance of most of the systems is not studied well and are found to be performing well in a particular range of speed. This is crucial in the safety device design and opens opportunities for research work. Third, with most automotive applications using IoT applications and embedded with cameras, the potential of using artificial intelligence and deep learning is immense and may result in more dynamic and better responsive systems. Finally, researchers need to develop cost-effective products as the current products fit advanced automobile due to the cost factor. This opens opportunities for researchers to use technology and develop affordable products and those that are to the reach of everyone.

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