AI-Based Systems for Autonomous Vehicle Nighttime Safety and Navigation

By Dr. Tatyana Lyalina

Associate Professor of Applied Mathematics and Information Technologies, Belarusian State University (BSU)

1. Introduction

Autonomous vehicles are expected as a way to reduce traffic-related fatalities. Nighttime traffic causes only about one-third of fatalities but more than half are pedestrian or cyclist fatalities, highlighting the need to improve nighttime safety for vulnerable road users. Extremely boost in sector investments and startup companies make their names. 3D sensors with fewer compromises towards resolution, fidelity and lacking light condition became cheaper and more available; a trend that LID-LAR instruments. However, this paper considers only work involving consumer cameras, either recorded or real-time and dealing with issues not present in daytime traffic, so it is also most relevant but adaptable to L- L, dAR or any future additions, including imaging fusions from multiple modalities. There are substantial insights in terms of research and applications following from night vision studies themselves, where census for collaboration in nighttime traffic data and night-time traffic simulations was published just slightly earlier than the COVID-19 pandemic started. That seminal effort sets the stage for tricky new night-time simulation, the now proven approach to narrowing the gap be-tween affordable and not overly obvious improvements in low-light imaging and the even repaid wheel after COVID-19 pandemic.

[1] [2]The ultimate goal of autonomous vehicles (AVs) is enabling substantial traffic safety benefits through elimination of driver error and state-of-the-art sensors (GPS, cameras, radar, LIDAR) to provide 360-degree coverage around the vehicle. In navigation, any sensor may in principle provide overtaking or obstacle detection, but only cameras can also be used for semantic segmentation, road markings, sign and traffic light recognition and, in combination with LIDAR, they provide obstacle classification, e.g., pedestrians. All of these capabilities except overtaking detection are relatively straightforward in daytime traffic. In nighttime

traffic, semantically apparent improvements preclude five times fewer daylight images, are challenging, even more so for AVs aiming at levels 4 or 5 automation that do not need steering wheel or pedals. Therefore, this paper systematically reviews multitudinous relevant contributions, supporting AV developers in planning and executing any innovative development of night-vision systems [3].

2. Background

Most existing machine learning models have been trained using visible light images collected during the daytime. However, the performance of these models would drop significantly when deployed in nighttime navigation scenarios because of the absence of light. This paper aims to train a model using the newly introduced Provident Vehicle Detection at Night (PVDN) dataset [4]. Meanwhile, to further enhance the performance, a cuckoo search based model is proposed to learn which hyper-parameters of Adaptive Histogram Equalization (AHE) have the significant impact on the sensitivity of the model [5]. The proposed dataset designed in the paper has 1000 normal nighttime images together with 1000 images with lighting intensity decreased by a predefined intensity, P. For 500 images, P is drawn randomly from U(0,255), and for the other 500 images, P is drawn randomly from U(0, P1) where P1 > 0 is the manually set threshold. Such a design can help to avoid the model detecting low-quality vehicle pixels as vehicle pixels with high confidence subject to the large P values. It thus also enables the training of a machine learning detection model with the capability of distinguishing the vehicles with high-intensity light being in front of a vehicle with low-intensity light without any performance drop issues [6].

2.1. Autonomous Vehicles

Most road fatalities occur in low-light, adverse-weather conditions, and inattentively. Such challenges are primarily with the driver of the vehicle. Dark transport infrastructure causing various low-visibility conditions is avoided, when possible, by developing infrastructure and specific transportation means (e.g., underground), but in everyday life dark accident sites can be found roadside or at crossings. Autonomous vehicles are supposed to be available 24/7 supported by AI. In our work, we aim to ensure this goal is kept and expanded beyond daytime operation by utilizing artificial intelligence and represent a contribution on the way to enable AI-based night operation of AVs. The consideration of illuminationrelevant conditions in transportation environments is becoming an IPv6-task, also within transport infrastructure [IPv6 Transportation Project-Task 2]. Here, initial steps are being made towards an initial exploration of AI-Solutions for endowing advanced in-vehicle illumination-sensitive competences to the AVs in the context to detect everything pertinent to light intuiting/archiving system observations, and to develop vehicles that can also learn how to handle the improbable autopilot (and vehicle SAE levels 0 to 5) operation field night on their own [IPv6 Transportation Project-Task 4].

(1300af1f-1ddb-48dc-8c33-e7d8f71bf609) in AVs can involve in-vehicle AI functions as well as infrastructure-based AI functions, enabling road vehicle automation and smart traffic control. Vital specifications for AVs, light for AV sensors including cameras, radar, and LiDAR as well as for the various light-based communication and data transportation systems being built in modern road transport infrastructures are described. As a result of the development activities, using vehicles as a sensornet and as computing-resources and challenges by the impact of malfunctioning vehicular in-vehicle functionality as well as external interfaces and infrastructure are pointed out as examples for entry points of research in vehicle AI.

2.2. Nighttime Driving Challenges

Exacerbating the difficulty of nighttime driving, most Advanced Driver Assistance Systems (ADASs) and Autonomous Vehicle (AV) configurations or algorithms are designed based on the configuration of the machine's sensors in daylight. Using the same configuration without considering the differences between day and night conditions leads to a dramatic reduction in the quality and capacity of configurations. Especially, with the expansion of Level 2 to Level 5 autonomous vehicle categories, which are based on different hardware and software configurations and are expected to operate in different conditions and situations, researchers have no choice other than to address this issue more seriously.

Driving at nighttime is different from driving during the day [7]. It is mainly due to the absence of natural light and the limited illumination from streetlights or car headlights. Low light conditions may negatively affect the performance and accuracy of sensors used in autonomous vehicles (AVs) such as cameras, Light Detection and Ranging (LIDAR), and Radar [8]. Not only are the sensors less accurate, but they are also unable to capture enough information to perceive the environment properly, rendering the exchanges of information that make the systems functional less reliable. Due to the lack of proper information, daytime configuration systems might provide very bad or, even worse, unsafe instructions.

Consequently, darkness turns into a challenging and limiting condition for AVs to perform "reliably", "safely", and "efficiently". As a result, this problem has received great attention in the research community and has most recently been the focus of a number of recent publications [1].

3. AI Technologies in Autonomous Vehicles

ADAS and autonomous use machine learning and deep learning to process large amount of data received through sensors and improve decision-making and obstacle recognition. For instance, driver assistance techniques can be utilized in the braking system, reducing the risk of injuries, and driving frequency and moveable distance determination are a couple of most substantial usages in ADAS [9]. Mediated perception, which segment will focus on, is when the mobile agent (in this case, AV) perceives the world using an internal model, while in direct perception the mobile agent relies only on the incoming stream of sensor data, such as cameras. On the other hand, localization is essential for autonomous driving and relies on matching sensor data with a priori maps to estimate the vehicle's position and detect obstacles. This one again depends on sensing modalities and uses a mesh of localization approaches, e.g., LD-matching, visual localization, self-driving GPS track networks, relying on data from sensors like cameras, radar,LiDAR or some hybrid [ref: https://www.evernote.com/shard/s386/u/0/sh/2ab1c98d-d6e5-42f6-a0d3-376fb47e97ba/].

Advanced driver assistance systems (ADAS) is a sort of additional system that is installed on vehicles to help drivers take action. As traffic incidents can occur at night due to drivers' fatigue or not being able to perceive any obstacles on the road, the importance of nighttime security systems in vehicles increases [10]. Hence, researchers have been focusing today, more than ever, to solve these security problems, and artificial intelligence (AI) approaches have been utilized for their solutions. As a result, advanced approaches are developed thanks to the precise localization, perception technologies processing the environment, and motion control, and Uber and Tesla Motors are the leading firms using advanced AI-based . There are three prevalent AI-based systems– sensors-based solutions, vision-based image processing, and a hybrid approach combining sensing and image processing [ref: https://www.evernote.com/shard/s386/u/0/sh/a5471312-7c36-49b6-8f27-fb761f9beefc/].

3.1. Computer Vision

Camera-based computer vision is considered to be the workhorse for the sensing part of an AV, thanks to its large Field of View (FoV), small form factor, high environmental adaptivity, including its relatively low cost and lightweight, and its extensive applications in the field of image processing and analysis using the already evolved Visual Information Processing (VIP) algorithm and databases. The computer vision awareness, at present, regarding at the development of computer vision perception module for ADAS mainly concentrates in sensing demand simulation, mainly for the data simulation for the perception algorithm validation and test of the neural network of the computer vision system [11]. Open-source computer vision datasets for ground objects like vehicles, pedestrians and cyclists, such as COCO and KITTI, are widely used in the relevant areas, for open-source computer vision datasets for aerial scenes, large quantities of following dedicated datasets, CityScapes, ApolloScape and A2D2, are usually used in aerial sense task areas. On the other hand, with the development and expansion of the field of computer vision and autopilot, datasets for more and more new tasks have been established and used, and this trend is increasingly prominent in recent years.

An AV is a vehicle capable of performing necessary safety and navigation tasks safely and completely on its own, without the need for human interaction [12]. In general, an AV mainly consists of sub-systems covering the sensing part, similar to how human eyes perceive the environment, and the control/execution part, similar to how human brain and muscles react to the environment. The computer vision is the most important sense that delivers a high-level understanding of the perceived environment. Computer vision refers to the process how a computer receives visual information, such as one or many images or video data and derives some understanding of aspects of the real world from such information. Such understanding includes, for example, detecting or recognizing people, cars, road signs, potholes, road boundaries, free space, etc., from perceived images.

3.2. Machine Learning

In the decision-making stage, traffic movement rules are used to ensure safe, comfortable, and professional autonomous vehicle operations. Models in which animations can be viewed three-dimensionally from the driver's or operator's perspective to make more intuitive autonomous driving operations can be developed by customizing the vehicle decisionmaking models as training data using ML. The vehicle speed and the surrounding vehicle or stationary moving objects are predicted by the so-called ML applications and a comfortable driving style is determined. ML applications are mainly used in autonomous vehicle technology for sensor data processing for vehicle perception, object detection, recognition, distance estimation, and localization, as well as for decision-making, object avoidance, and vehicle movement prediction via addressing features [10]. In all of these applications, the models are trained with sensor data as labeled. If label data are insufficient or if the training process is slow, the model loses its generalization feature, thus leading to operations not undertaken professionally on real roads. Improvements in processing power are aimed to be achieved using ML by customizing the architecture of the DL model used in applications, routing the training data correctly, and using it efficiently.

Obstacles, autonomous vehicle stability, and all other environmental elements—such as traffic rules, pedestrians, animals, and public and private vehicles—can be seen as obstacles in autonomous vehicle road surveys. The vehicle environment can be surveyed via multiple sensors (millimeter wave radar, LiDAR, ultrasonic sensors, infrared obstacle detection, and night vision systems), in multiple dimensions with the help of sensor fusion [13]. While 2D obstacle detection is generally preferred for real-time application performance, surveying in 3D is most accurate. In the autonomous vehicle decision-making process, the perception stage enables the detection of objects of different types, directions, and sizes. Lane detection is also another important aspect of object detection. Traffic lights and signs stand out among the objects detected. The localization of the vehicle is also important to ensure the safe, comfortable, and fast operations of autonomous vehicles. Here, extra technical foresight is required to handle the many different problems under real and virtual circumstances, especially in three-dimensional and crowded autonomous environments. In order to ensure that any detected obstacles are not hit by the vehicle, the vehicle control systems apply special algorithms to calculate and reach a safe distance in use cases such as Parking and Coordinating for breaking or stop operation, and Predicted time-to-impact for priority operations. Otherwise, simultaneously entering intersection and helping the right of road are important issues in which the vehicle's decision-making system is realized [14].

3.3. Deep Learning

The network will involve a few high-level features (like in Deep Learning) which makes it cost-prohibitive for the synthesis of a few prototypes. Convolutional neural networks (CNNs) records are used for the conversion tasks. Technology terms and computerised architectures have increasing importance in disaster relief applications. They can navigate using different kinds of function and ones used for neural network training. They are used in image recognition and other sources as well. The neurons in CNN learns about the features from the images, from primitive edges to more complex details like wheels of the car as in this project.

The scene representation.

Convolutional neural networks (CNNs) are a type of artificial neural network that have especially become dominant in modern computer vision applications [15]. The idea behind the architecture is to use a sparse matrix, or "filter," to convolve with the input using a first-time complex-valued factor, also referred to as kernel to create a new matrix. This new matrix can be thought of as a graphical representation of the paint, but also capturing local spatial hierarchies. Convolution operator in a neural network is a technique used to execute a very important operation on the input image and ensure that various features like edges, gradients, and intensity are taken out.

4. Nighttime Safety Systems

Automated vehicles have seen considerable progress over the past decade and have become a trending topic. It is expected that the future role of humans in driving will be satisfied by the artificial intelligence systems based on Automated Vehicles (AVs) [16]. However, advancements in this industry are facing several hurdles. The technical bottlenecks in questions mainly confront nighttime and adverse weather conditions. To overcome these limitations, recent attention has been devoted to the development of solutions for nighttime safety and navigation of AVs. Nighttime and adverse weather conditions typically worsen the visibility conditions, leaving the computer vision engines blind to recognize the objects lying along the traffic infrastructure [17]. Nighttime detection of vehicles is mainly composed of Shape and Pattern-based methods. Blob detection using Haar, HOG, CNN and such has been proved efficient on large available datasets. Adversarial examples formulated as driving scenes aiming to confuse the current autonomous drive models on daytime or adverse weather conditions have been posed by researchers, which make the system raise a false alarm and lead to accidents. Pattern-based techniques have unsatisfactory performance as they may not describe the light reflections caused by oncoming vehicles. More precisely, when the semantic segmentation engine is unable to discuss two distinct vehicle boundary boxes properly separated in the same frame, a vehicle collision recollection can occur [4]. For AVs to be widely adopted, they have to deliver consistent comfort and traffic safety on every traffic infrastructure with ignorance to the weather conditions and whether the time of the day is nighttime. Nighttime and bad weather conditions severely degrade the visibility during street traffic monitoring. The state of the art daytime models usually fail to recognize the pedestrians and vehicles that are visible under the traffic street lights at night.

4.1. LiDAR Technology

Manufacturers of these lasers have realized the potential opportunities of embedding intelligence into the sensors themselves. This can change the current approach to sensor fusion, potentially moving away from the use of multimodal dependencies with others sensors to having a self-contained smart sensor leveraging new ways of designing perception networks by adding depth information in part of the design, using more or less relevant layers in a multi-task learning manner, with only limited or even minimal additional computation. As for the ownership of the generated data, it is likely that the changes in the paradigm will allow the end customer to bypass the need for proprietary data for local training of the perception systems, thus opening up new market opportunities for companies who do not have the data storage capabilities of current companies in this field [18]. And even though these developments are mainly strategic, they will represent most of the innovations in the field. At present, it is too early to predict which implementation will become the main standard, but it is important to highlight the recent trends to raise awareness. Moreover, regardless of who is the data owner, Europe should not be passive in the AI field, and as such it is good to see that a European consortium such as AVL and Sony are looking to develop and build on the development of LiDAR components and supply chains.

As an active sensor, LiDAR performs better than vehicle camera, millimetre-wave radar, and ultrasonic sensors in terms of anti-electromagnetic interference, and night vision [19]. However, its ability may be affected by the weather, but its actual ability is already relatively perfect for the time being [20]. Moreover, the automotive industry has been largely dominated by silicon electronic technology. Along with the development of deep learning algorithms, these challenges show the potential of the realization and protection of information security for autonomous driving in the future. LiDAR is potentially one of the most expensive sensors included in the automation package on current production vehicles not only for the individual unit but also due to the need for a redundant sensor on either side of the car for safety reasons. It will therefore be interesting to see how the technology around LiDAR sensors will develop over the coming years. The increasing amount and quality of information available from

LiDARs and their naturally advantageous capability should soon facilitate further developments such as ubiquitous digitally augmented maps, 3D imaging in a large variety of scene imaging, improved privacy, improved segmentation tasks and network designs through the addition of depth information, better long-range detection due to structured resolution and the possibility to observe thoracic/see-through data for improved vehicle behavior estimation or intervention for likely occluded areas.

4.2. Infrared Cameras

The study clearly demonstrates that NIR-based systems are very effective in detecting objects during the night. In the future, the driver's line of sight may be improved thanks to infrared light, which will result in improved results in many other natural situations. The temperature of the human body must be taken into account. IR cameras perform better than other nighttime vision cameras due to their potential to deliver steady and consistent results from one scene to another. Eventually, the configurations of future IR cameras and onboard cameras in a vehicle will include data from a variety of traffic systems. These systems will share a number of goals, including increased passenger safety (active and passive) and the optimization of power levels. Therefore, these goals shall be realized by incorporating additional data from other surveillance devices so as to improve the functioning of several components such as road infrastructure, intersections, and surrounded vehicles while avoiding pedestrian and vehicle crashes. The future of the study of NIR cameras and nighttime vision is indispensable for the forthcoming year's ecological and inexpensive electric autonomous cars, which will start to be manufactured in the future [21].

[22]To offer a response to this, the performance of IR cameras in a variety of ambient light conditions was evaluated. When examined through an IR camera, night scenes are much brighter, and people and vehicles are easily distinguished. In addition, IR cameras are capable of delivering consistent and unchanging results in a variety of environments, from dimly lit to pitch black settings. An enhancement was made to generate Enhanced-Light Video Detection from Early Recognition of Distant Cameras (ELVD-ERDC). Since ELVD and ERDC methods contribute to considerably superior nighttime intelligent vehicle navigation when compared to existing nighttime vision, this can help improve night-time intelligent vehicle navigation. Near-infrared (NIR) cameras were found to be more suitable for a night-time vision technique since they used an internal light to refresh visual information [23].

4.3. Sensor Fusion

Short-range radar sensors have effectively increased the robustness of the original environment perception in Raptor (Rapid Autonomous Profiling Technology) and decreased the error rate in Kaist-VTT (Vehicular Traffic Foresight by Intelligent Intelligent Technology) in lane-level positioning and signal point detection, and patch-point-patch and scanline LIDAR points have effectively adjusted the direction and distance deviations of street signs, wires, and curbs in Row 1 and have improved the improvement of pseudo box size. Besides, as shown in row 9, radar can work in bad weather and can also reduce the industrial depth deviation caused by low textured surfaces in bad weather. So, improperly fusing the rubber sensor radar with the cubic sensor camera and LiDAR, as done in Kaist and Luohu, oracle-loss results will be produced in this process and thus might waste the resources of technical competition in 1st and 3rd places [24]. The poor generalization ability of the training model using original images with labels will decline detectability and impact the detection performance in completely dark environments. Since the affinity target with the same real Doppler velocity interval is finely aligned for fusion in rows 6 and 8, the application of long-term moving stationary radar and SPEED limit sign radar sets up an interesting pretrained fusion model of whole-road and object layout. All radar features are then directly precipitated into a robust long-term environment perception enhancing object detection list. So embodied roadside radar can maintain the background feature and afford decision reference information. Therefore, many timely interactive pseudofusion physics can be constructed under the fuseconflict threshold. HAM is the main probing vision real radar depth sensor in the environment Intelligent Technology Technology Laboratory (ICTL) on the Taiwan and Hong Kong racing car platform, it will explore the offline into online and medium-range into long-range radar session multi-source signal history body reorganization methods and chassis target formation methods. The related coordinate transformation and data association between the coordinate of the weirdAdis of the sensor and the three-dimension and the region attention detection methods of the virtual deduction equation are realized in the above. In the future, we will try the road radium curve aware 3D-vehicle feature extraction method for radar coarse and fine descriptor objective classification. In this way, we will finish the car network sports pedestrian point detection based on the following point projection from the point-after fusion matching stage method [25].

Since there are several types of basic road facilities located on the road side, a real roadside cooperative perception system should be built to adapt to various complicated road scenes in autonomous driving [26]. A dense real-time multitype and multigroup roadside sensor monitoring system with different quality sensors in various road scenes will be an essential component for all-weather dynamic environment perception. In this paper, distributed roadside multitype sensor perception capability and its result fusion to support HD perception in the dark and dynamic roadside environment for autonomous driving is studied. We plan to investigate the potential of roadside LiDAR-RGB image fusion and short-range radar camera LiDAR fusion of multigroup roadside sensing data in a real driving scene. Therefore, using some 3D point clouds in Row 1 and pixel-loss-range LiDAR points in Row 2 as one complementary pair can well supplement the lost projection target and myriad projection target, and local target can be well linewise associated within and between the pairs. Without needing to care for label and target data used in previous methods, the final non-maxima suppression (NMS) filter outputs directly such positive prediction results. The STUD point detector in row 8 can well solve the verification and long-range coverage problems with roadside sparse and sampling data. To enhance the performance and performance stability of the forward propagation inference model in Fig. 4a during dark road scene navigation, the pretrained lightweight model is solely used as a special early light motor for illuminating the dark road. To deal with the scenario of insufficient RGB information corrupted by rainy images, a monochromatic thermal image is inversely projected to a pseudo-color RGB image without losing any object information for reverse input. As a result, based on the abovementioned purpose of properly fusing different group and type roadside screening data of the top layer of the fusion detection branch, this emissive side uses the top layer lightweight 3D tracking model in Fig. 4a to achieve this fusion process of fine alignment and interim mutual restraint of various group-type roadside tracking targets to solve the problem of misalignment of multi-sensor data in autonomous driving.

5. Navigation Systems

Convolutional Neural Networks (CNNs) are increasingly being used to perform tasks related to computer vision and artificial intelligence. By combining some of the most advanced machine learning techniques and creating a stacked classifier in a gifted architecture, we conducted night-time driver behavior prediction using taillight signals present in rear views of following vehicles. We prove that this approach provides excellent prediction performance even though we removed the license plates of the followed vehicles [1].

Computer vision and perception algorithms process sensor data to generate environmental perceptions for vehicle navigation systems. With color or grayscale images, these lateral distortions may be severe. For vision-based nighttime vehicle detection, the traditional HOG method has been widely used, but it does not perform very well when the gradient magnitude in the edge direction is very small. In this paper, we extend the basic HOG algorithm to generate improved HOG features [6].

5.1. GPS and GNSS

[27] Satellite-based global positioning systems, such as GPS and Global Navigation Satellite Systems (GNSS), are prevalent in the context of the safety and mobility of connected and autonomous vehicles (CAVs). This is highly likely to remain the case in the near future [6,8,9]. The prediction of 40.2 % CAGR of the global indoor virtual testing market for CAVs from 2025 to 2030 is saturated with the use of GPS. These satellite-based technologies are prevalent because they provide effective, simple, passive, and economical positioning and navigation solutions to CAVs, given their several possible location-determined outliers requirements and decimeter level of precision [92,93].[28] The functions of GPS and GNSS also extend beyond providing precise positioning and navigation solutions to CAVs. GPS and GNSS also offer vehicle-to-infrastructure (V2I), vehicle-to-vehicle (V2V) and vehicle-to-pedestrian (V2P), which altogether are branded as vehicle-to-everything (V2X) communication. However, the performance of GPS/GNSS is degraded in tunnels and when a CAV's GNSS signals reflect off tall buildings in the urban environment. The above statement states that the existing and further developments of electrical energy sources will play a key role in the application of CAV with GNSS. In addition, V2V and V2I communication might also be affected.

5.2. SLAM Technology

In real-world scenarios achieving highly accurate robot and uav visual localization, still represents a challenging task as it is influenced by many and often not predictable factor such as season, weather, robot perception quality and realism of the considered environment. Considering ds-slam in the larger, higher level and complex problem of mapping, we can capture the meaning and relevance of the environment in a much better way, using higher level, distinctive and stable groups of features called key poses or keyframes groups.

Keyframes are places recognizing the environment of the robot, but also, more surprisingly, the environment trajectory and shape [29].

This work discusses a visual odometry method where visual features are expressed in terms of Lines, which are the most stable geometrical features of the environment and can be associated to try spike symmetrically in monocular images, in order to achieve purely monocular Simultaneous Localization And Mapping (SLAM) performances. Then, our multi-hypothesis low-complexity robust, resilient and efficient visual global localization and SLAM so-called Line-SLAM was tested on the EuRoC and KITTI datasets [30]. A visual localization system is highly essential for robot and uav autonomous navigation. An incredibly amount of detailed and relevant works were published in recent years showing the cutting-edge of all the localization methods and algorithms, a technological breakthrough only made possible by the union of the latest extraordinary advances in both computer vision, artificial intelligence and deep learning domains.

5.3. HD Mapping

In conclusion, we approach the problem of building photorealistic HDF-Maps in cluttered driving scenarios. Our work introduces a novel method for automatic object-based 3D HD HD Map construction harnessing modern computer vision techniques. Besides our object-based HD Map, we also introduce a fully automatic alternative which is based on 3D surface points only. We show that both approaches are able to rely exclusively on data obtained in the 3D perception process of the autonomous vehicle.

Currently, HD maps are manually annotated, which is time consuming, not scalable and prone to human errors [31]. To address this challenge, several computer vision and machine learning techniques have been investigated. These techniques are mainly categorized into two types: object-based and surface-based methods. An automatic object-based annotation of HD maps is proposed based on a fusion of analysis of the trajectory data captured during the 3D perception system construction and/or various detection results generated by deep learning network models. In addition, a method for a fully automatic surface-based object detection and annotation is proposed as the second stage of the annotation pipeline for many real images where the deep learning technique may show the limitations of detection [32]. These objects can be detected within point clouds using a pre-trained deep learning network. Subsequently, points are extracted within their detection bounding boxes for the following pipeline, and they are predicted with a shallow 3D semantic segmentation network called SemanticExplorerNet.

6. Challenges and Limitations

Since the magnitude of environmental irregularities and illumination intensity with respect to the day time images is quite different and the low luminance display properties in night time can be a propagation channel for some undesirable issues like, improper road visibility, low contrast ratio, and very low local structure and pattern characteristics and can result in a high probability of accidents in the night. At night time the total light in a scene having very low luminance makes the distribution with respect to the background region of high intensity and widely spread out intensity values images. Such relocating appropriate pixels from the total set of feature vector could become more insightful due to inadequate lighting condition due to limitations of direct or indirect lighting on the target in low luminance region [21]. You can experience noise in the low-luminance areas under limited light conditions leading to the inability of the system at recognizing the appropriate local structures and pattern properties also, with the advent of small secure and large capacity equipments large capacity lithium ion batteries that are light are available in the market and hence it has become possible that many types of imaging devices are being provided with a built-in flash illumination mode, which allows the camera to illuminate objects based on user requirements or based on automatic systems.

Luminance is the intensity of the light incorporated into the camera sensor per unit area, for day time scenes luminance can appear to be quite variable depending on the source of light. So, even under a very stable illumination condition, the luminance of daytime image can exhibit significant variations due to factors including – the irregular shadow patterns on the ground and road surface, arbitrary sunlight and environmental conditions such as mist, fog, and rain. However, for the night time scene, the intensity of light incident on the camera sensor per unit area becomes an important constraint. At night time, the streets have a low luminance level as the moon reflecting intensity on the sidewalks and the road surface is not consistent, and the flow of vehicles, people walking, trees, vegetation and the color of the road have very low luminance properties and the total light is generated by the vehicle headlights. This kind of unpredictable and oblivious light patterns and irregular light source can lead to the significant vulnerable process of the visualization process in night time images [7].

6.1. Environmental Factors

In the counterfeit of night driving, the environmental factors–the illumination of the scene and how dynamic shadows are distributed are more challenging. Perception reasons, spatial discontinuity of shadowed areas is highly challenging for depth estimation and object detection techniques under such limited-light conditions. Besides, it is also a difficult source for finding the layout of the scene and localizing on the map. A variety of light sources or reflections (activating the specular supervision) to change the scene texture also complicate the vision of the quest. With the move towards night driving, various difficulties will be posed on navigation decisions: in addition to the presence related to traffic, conceptual knowledge on the lateral region in an urban offline illuminance can also be essential in making the safest choice. Reducing light pollution is also part of this study. Although a non-negligible number of streetlighting and headlight removals are expected, the study does not quantify the exact lighting modifications directly. It is nationwide that the demand for the application has been opened in a realistic manner while the set up for alternative navigation algorithms and sensors has started. [33]

Though the progress in autonomous vehicle development has been thriving, major achievements are limited to scenarios of good lighting on ideal, structured roads. The concept of "level 5" described yet another evolution goal to reach the limit of fully autonomous operation. Though this concept makes the previous notion of design exceptional, efficacy of different sensor technologies, navigation and safety system is required to be significant. The application of deep reinforcement learning, which has capacity to handle uncertain, complex scenarios, comes into necessity. However, while computer vision and deep learning have performed well under ideal lighting, restricted holistic navigation scenarios and related challenges. The present paper focuses particularly on addressing this issue: challenges encountered in nighttime scenarios, where the vehicle is faced with limited illumination. [7]

6.2. Technical Constraints

Adverse weather adds another barrier and only 9% of the top surveyed organizations purport to handle adverse weather using deep learning models. Both organizational and general reports suggest adverse weather conditions reflect major technical and systematic issues. 89% of organizations piloting adverse weather conditions report lighting as a technical constraint. 79% of organizations piloting severe weather conditions implicate fog. 71% of organizations with intermediate capability admit snow and rain represent problems. Accordingly, deep learning based depth completion, VPR and IMU based ENIO can accurately ameliorate system operations under adverse weather conditions. One Italian company validates their de-raining network by reducing their depth predictions error by 11.0% during a light rainstorm while a second Italian company aims to improve rain's detrimental effect by decreasing error rates by up to 30.0% in adverse conditions [34].

Severe technical and physical constraints are holding back the development of fully autonomous urban operations at night. Establishing efficient and mature semantic segmentation, object recognition and depth completion networks to ensure excellent perception at night is one of the main technological barriers. Many researchers see this as a key and unsolved problem. The severity of this problem is clear from the fact that while numerous organizations claim to have nearly reached full operating capacity during the day, few have piloted urban operations at night [16]. Given the difficulty of the problem of developing nighttime machine vision, some researchers are resorting to the use of LiDAR sensor towers to avoid sensor-specific issues such as lighting, adversarial vision and other physical constraints. As a reliable, all-weather sensor, LiDAR often provides the point cloud on which to build a vision system or to directly input the point cloud into an algorithmic prediction framework. An accurate and high-density LiDAR can represent the details of a point cloud in a rich and detailed manner creating a robust pipeline for tracking, detection and SLAM under varied weather and lighting conditions [35].

7. Future Directions

[10] The development and implementation of AI to support connected and autonomous driving (CAD) is an enormous interdisciplinary challenge. [36] CAD technology requires an inter-disciplinary approach to support motion planning, localization, perception, and decision and control in increasingly complex traffic scenarios. Although CAD functionalities are developed with safety in mind, important uncertainties in the real-world traffic environment are still unresolved. To achieve truly autonomous driving, a lifetime learning framework will be essential to improve robustness, safety, and security throughout the life cycle of a CAD system.[33] The lifetime learning framework will be mandatory to maintain safe operation of CAD systems over the long-term, despite a growing mixture of legacy and new model vehicles in traffic and use-cases that have not been considered during the initial development of the system. Furthermore, concepts and modules at the heart of autonomous

driving, such as sensor processing, situation understanding, motion control and learning, range in complexity from rule-based and model-driven to data-intensive and AI-driven statistical or ML models. The implementation of AI models with ethical implications in CAD systems requires continuous re-evaluation and update—making transparent lifetime learning an essential feature. At the same time, this framework has to be able to guarantee that extended analysis of mature systems and outcome of continual learning is not continuously re-triggering recertification of the CAD system. Creating transparent and interpretable safety enhancing and security requirements compliant CAD systems will be a major enabler to realize the international approach in a reliable and efficient manner. An important factor with regard to general reliability and trust in AI models is their development processes, the simplicity sufficient for obtaining information to enable a full safety review of the AI model, and its deployable implementation.

7.1. Advancements in AI Technologies

In the second phase (deep learning and intelligent phase) from 2010 to now, both navigation and perception approaches have rapidly evolved using deep learning frameworks. Availability of effectively annotated exploration datasets, such as KITTI [14], Audi A2D2 and LISC, have accelerated the development of a multitude of object detection methods where convolutional neural network (CNN)-based detection and segmentation models have gained popularity. Similarly, simultaneous localization and mapping (SLAM) was also effectively treated with different CNN frameworks. At the control and motion planning layer, improvements by incorporating neural network and reinforcement learning (RL) have been succinctly observed. In addition, for sensor fusion and data association or fault detection, improvements have been reported. Consequently, AVs from both academia and industry were put on the roads and intense testing was performed at available international testing zones under different environmental conditions.

In recent years, the automotive industry has been revolutionized, with autonomous driving at the center stage. The goal is to improve safety by avoiding driving errors caused by human factors, and in parallel, to improve the quality of road transportation by reducing traffic jams, energy consumption, and emissions. As shown in Fig. 1.1 [7], the evolution of autonomous vehicle (AV) systems has passed through two phases primarily enabled by the advancements in AI technologies. In the first phase (historical phase) spanning 1980–2010, AV development was enabled by rule-based systems, separate and crackable application of different sensors, and planning/control methods. Followers, such as dSPACE and National Instruments, commercialized some standard systems (e.g., sensors and processing units) that are now used as components in AV research and development.

7.2. Regulatory Frameworks

The recent developing of cyber-physical systems has addressed a lot of new research and many regarding safety of vehicle on field, especially about machines and physical interaction. The field of machine safety, including emergency stop, safe robot zone and shared zone between machine and human is now well-defined and standardized. Other two important elements that have been farly developed are the fault diagnsis and the safety communication for the security of the vehicle [37] Very essential element such that designing not only for safety but also for the security of the AI system, such as against collision, intrusion and attacks by a large part of the scientific computing community and cyber security communityThe third element explored by automotive are formal methods and the various techniques to guarantee safeness in complex coordinated control systems in the context of connected vehicles with V2V communication, or human interaction, very challenging in terms of robustness.

The emergence of autonomous systems led to the establishment of new regulatory frameworks, such as the The General Data Protection Regulation (GDPR) [38] and the guidelines provided by the National Highway Traffic Safety Administration (NHTSA) [39]. In the United States, the Secure and Trustworthy AI in Automated Systems (STAARS) act was passed in 2021 and proposes to ensure the proper design, validation, and approval of AI systems that support critical operations. However, such regulatory frameworks tend to be very general and do not yet provide specific standards or detailed requirements. Moreover, there is a debate on which measures should be adopted to make AI systems safer. There is a certain degree of consensus on the fact that AI should be designed to be safe, robust, and performant. Yet there is no agreement on how such measures can be obtained. So far, the vast majority of measures are based on functional safety and require the execution of random failures testing scenarios. In modern AI-driven systems, such safety concepts, which are based on concepts of probability and statistics for representing and assessing safety, are sometimes problematic. This new era of standards and certification of AI-driven systems introduces new challenges for the R&D. Along with developing functional safety standards, it will be needed to develop methods and approaches for the safety qualification of machine-learning models that are getting to be widely used in on-board systems of vehicles and smart robots. The

ISO/PAS 21448 offers some guidelines in this sense; however, these guidelines and at practical levels are yet open to new developments.

8. Conclusion

Different AI-based nighttime aware approaches to improve the performance and robustness of LiDAR-based nighttime vehicle detection using an HD map were well reviewed and evaluated. Nighttime driving scene components were used for both object detection, segmentation, and tracking in a real-time multi-agent trajectory prediction system. The result suggested that nighttime-aware HD mapping approaches or pure camera-based nighttime perception approaches were also seen as an alternate to the allowance or complementary to the LiDAR-based nighttime perception [23]. These studies are conducted using real-time LiDAR and camera image data. Moreover, other night vision sensors such as thermal cameras, radar, should also be fused and these components when present should also be studied all together to mitigate their mutual weaknesses in night traffic perception.

The usage of artificial intelligence (AI) techniques for autonomous vehicles (AVs) during night-time has become an active research area as these systems need seamless performance and robustness under varying environmental conditions in improving AV's nighttime driving capabilities [40]. As an essential task for AVs, object detection in night-time AV driving systems continues to attract researchers working on different sensor modalities and across disparate domains with a considerable focus on LiDAR based approaches for AV object detection during night-time driving. An adaptive vision-based intelligent darkness driver assistance system (AVIDAS) is also proposed with a heterogeneous dual-core (ARM-DSP) embedded computing platform for integrated vehicle detection, collision warning, and traffic event recording to improve driver surveillance in different night road environments and traffic conditions [5].

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