

Review Article

Driving in the Rain: A Survey toward Visibility Estimation through Windshields

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Rain can significantly impair the driver's sight and affect his performance when driving in wet conditions. Evaluation of driver visibility in harsh weather, such as rain, has garnered considerable research since the advent of autonomous vehicles and the emergence of intelligent transportation systems. In recent years, advances in computer vision and machine learning led to a significant number of new approaches to address this challenge. However, the literature is fragmented and should be reorganised and analysed to progress in this field. There is still no comprehensive survey article that summarises driver visibility methodologies, including classic and recent data-driven/model-driven approaches on the windshield in rainy conditions, and compares their generalisation performance fairly. Most ADAS and AD systems are based on object detection. Thus, rain visibility plays a key role in the efficiency of ADAS/AD functions used in semi- or fully autonomous driving. This study fills this gap by reviewing current state-of-the-art solutions in rain visibility estimation used to reconstruct the driver's view for object detection-based autonomous driving. These solutions are classified as rain visibility estimation systems that work on (1) the perception components of the ADAS/AD function, (2) the control and other hardware components of the ADAS/AD function, and (3) the visualisation and other software components of the ADAS/AD function. Limitations and unsolved challenges are also highlighted for further research.

1. Introduction

Intelligent transportation systems (ITS) and the development of intelligent cars, often referred to as smart cars, have revolutionised the automotive industry. These technologies take advantage of cutting-edge computing, connectivity, and automation to improve road safety, optimise traffic flow, and improve the overall driving experience. In this context, visibility estimation and warning systems play a crucial role in ensuring the safety and reliability of intelligent cars, particularly during adverse weather conditions such as rain.

Rain affects driver visibility in a variety of ways but is most detrimental at night and has an immediate effect on visibility. According to the Met Office, 9 out of 10 deaths and serious injuries related to weather occurred on roads during

rain, even moderate rain can reduce your ability to see and be seen [1]. Rain can alter visibility through its effects affected by headlights, windshields, road surfaces, and road markers. An object is usually visible when light from a source, such as the sun, street lamps, or headlights, bounces off it and back to the eye. Rain has many detrimental effects on this process; for example, it reduces the effectiveness of headlights and other light sources by filtering off some of their light output and obscuring the road ahead. The layer of water filled with debris that passing vehicles splash on the headlights may further reduce the lighting efficiency. When the raindrops are struck by light, only a fraction of them passes through, whereas the remainder disperses. As a result, some of the light reflected by objects is blocked, resulting in less light reaching the driver's sight. A portion of the

headlight light is reflected by the driver's eye through "backscatter," or light reflected by rain, which serves as a curtain, reducing the contrast of anything within the field of view. The rain then obstructs the return of light from items on the road, decreasing their contrast due to back-scattering effects. Additionally, backscatter produces glare, which is characterised as the light that is substantially brighter than the driver's dark adaption threshold. Glare produces visual discomfort and affects contrast visibility. Glare affects vision in all drivers but is particularly harmful to senior drivers. Due to low vision, individuals focus their attention immediately ahead to view their destination. This reduces the likelihood of detecting anything within the peripheral field, making it more difficult to spot a vehicle or person approaching from the side. Rainwater smooths the rough edges and creates a mirror-like surface on the road. When the headlight beams come into contact with the road, they reflect forward rather than backward. The road seems darker, making it more difficult to spot people wearing dark clothing as their contrast is reduced. The mirror finish of the road also increases the likelihood that light from other sources, such as street lamps, business signs, or other cars' headlights, would beam directly into the driver's eyes and generate glare.

Furthermore, intelligent cars can incorporate ADAS which utilise artificial intelligence and machine learning (ML) algorithms to enhance safety in various driving scenarios, including rainy conditions. These systems can provide real-time alerts and warnings to the driver, assist with lanekeeping, and apply emergency braking if necessary. By continuously monitoring the surroundings and analysing data from multiple sources, ADAS can help drivers navigate safely through rain and other challenging weather conditions.

ADAS/AD functions used in semi- or fully autonomous driving vehicles consist of the three main components of *perception*, *control*, and *visualisation* [2]. These interact as depicted in Figure 1.

The perception components consist of software and vehicle sensors that are used to understand and estimate the driving scene and road conditions. Control components mainly involve the hardware used in-vehicle steering and navigation [3]. The visualisation part is the newest of the three used in the communication between the ADAS/AD functions and the driver. At the heart of all these, three ADAS/AD functions are object detection [4]. The driving scene and conditions are interpreted, and then, the detected objects are converted into an object list from the perception components. Then, the object list is processed by the control components, who will translate the object coordinates and other dimension information into navigation and steering commands. At the same time, the list of objects can be used by the visualisation components to communicate with the driver steering the trajectory paths, potential collision avoidance and evasion prevention alerts, and other information related to the infotainment. Therefore, on all types of roads, visibility is an essential element of driving activity, and a decrease in visibility affects the reconstruction of the

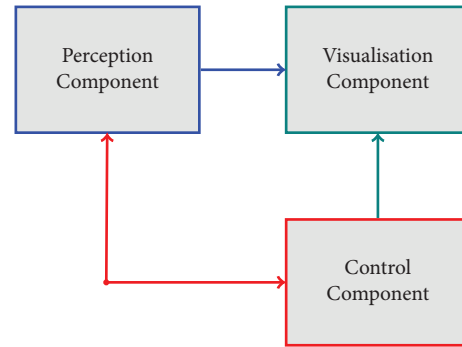


FIGURE 1: The three perception, visualisation, and control ADAS/AD function components and their interaction.

scene and consecutively the list of generated objects used by the ADAS/AD functions.

This survey focuses on methods for estimating visibility in real time using deep learning and simulation-based approaches that can be either model-based or data-driven. Automated visibility detection and warning systems are critical tools to identify and respond to reduced visibility caused by precipitation, which can increase the risk of accidents. However, such systems are not yet widely deployed, resulting in a significant number of fatal accidents in areas without them. While most research on autonomous vehicles has focused on fully autonomous vehicles, there has been limited attention given to human drivers' perception and semiautonomous vehicles. We argue that the human perception component in the rain is another key point in semiautonomous and fully autonomous vehicles and should be further investigated. To shed more light on the current state of the literature, we present a survey highlighting deficiencies in current studies, thus calling for more emphasis on some specific areas, including visibility estimation for ADAS integration, and suggesting how the literature can be integrated into these ADAS components. Unlike previous research from the 1970s to the 1990s [5–7], which focused on determining speed limits in the rain, the main focus in recent years is concentrated on improving exterior sensors for level 5 autonomous vehicles in adverse weather conditions [8–10]. Moreover, most research on visibility estimations is particularly focused on fog [11–13]. However, this survey does not cover the exploration of fog-related research. Another crucial aspect not considered is the human driver's visibility from inside the vehicle looking through the windshield in the rain. Therefore, the objective of this survey is to explore the development of more effective visibility detection and warning systems by evaluating and analysing current visibility estimation methods. Our goal is to identify the physical factors that contribute to reduced visibility and classify them by their respective ADAS components, thus enhancing driver safety and reducing the number of accidents caused by reduced visibility.

The remainder of the study is arranged as follows:

- (i) Section 2 presents three topics of discussion, first the causes of visibility reduction in the rain, scene

- interpretation and reconstruction, and finally the ADAS hardware
- (ii) Section 3 discusses the role of sensor performance software for deraining
 - (iii) Section 4 presents an analysis of current rain visibility estimation solutions
 - (iv) Section 5 provides a comparison of visibility systems and groups them into the three aforementioned ADAS categories
 - (v) Section 6 concludes the article by summarising and discussing relevant outcomes from this study
 - (vi) Section 7 highlights areas of improvement that need to be investigated in future works

2. Rain Visibility Estimation Systems

2.1. Physical Factors Contributing to Reduced Visibility on Windshield and Perception. Visibility is reduced by rain on the windshield, impacting the driver's perception of the surrounding environment. This reduction in visibility due to rain can introduce challenges to the driver's perception, increasing the risk of accidents. Studies, such as the one conducted by [14], have examined the association between decreased visibility and crash risk in real-time visibility conditions. The findings highlight a significant percentage (95.4%) of vehicles speed under low visibility conditions, which significantly increases the likelihood of rear-end collisions if the leading vehicle does not abruptly stop, as most vehicles may not be able to stop in time due to reduced visibility.

Perception plays a crucial role in responding to driving conditions, including reduced visibility caused by rain. The driver's perception of the environment is influenced by factors such as raindrop size, lighting conditions, and their individual visual acuity. These factors can affect how the driver perceives and interprets objects, distances, and potential hazards on the road. It is essential to consider both the physical factors that contribute to reduced visibility and the driver's perception when assessing the impact of rain on driving safety.

However, accurately quantifying the impact of rain on visibility and perception can be challenging due to the complexity of the factors involved and the subjective nature of the driver's visibility experience.

2.1.1. Rain Intensity and Properties of Rain. Rainfall intensity (RI) is a measure of the amount of rain that falls over time. The intensity of rain is measured in the height of the water layer that covers the ground over a period of time. According to the UK Met Office [15], there are four types of rain intensity classes, namely, light rain (LR)–less than 0.5 mm h^{-1} ; moderate rain (MR)– 2 to 10 mm h^{-1} ; heavy rain (HR)– 10 to 50 mm h^{-1} ; and violent rain (VR)–greater than 50 mm h^{-1} . The raindrop must be larger than 0.5 mm in diameter to be classified as rain, and the visibility distance in rain decreases as the intensity of the rain increases [16, 17], and this tends to be due to the physical properties of the rain

(PoR) hitting the windshield, which tends to blur and distort the background and objects [18]. Additionally, rain decreases the reflectivity of most materials. Because less illumination is reflected back from the object, the items look darker and have less contrast. Pedestrians dressed in dark clothing would become considerably darker and perhaps harder to notice. Rain also has an effect on vision because it alters the amount of light that reflects off the road and bounces back to the driver's eye. Road markers, such as pavements, are obscured by rain. A reflective component is included in the paint used to produce road markings. The reflective coating reflects headlight lights back to the driver's eyes under dry conditions. Water, on the other hand, acts as a lens, scattering light such that a considerable percentage of it is reflected in several directions. As a consequence, the lines are almost invisible to the motorist. The same effect causes the road to look darker. The surface of a normal road is rough, causing part of the headlight beam to reflect back to the driver's eyes.

2.1.2. Vehicle Speed. The visual impression of the intensity of the precipitation continues invariably while you remain immobile. When moving in a certain direction, an increase in rain intensity is perceived due to the coalition with or passing through raindrops at a rate proportional to the speed of motion. The perceived severity of the rain is directly related to the number of drops with which you or your vehicle collides; the faster you drive, the more raindrops clash with your windscreen; the more raindrops that collide with the windshield, the less the driver perceives the world, this is known as the relative velocity.

This phenomenon is intuitive and can be explained formally simply by noting that an individual raindrop (falling vertically at a speed v_{rain}) hits a vehicle (travelling at a speed whose horizontal component is v_x) with a perceived speed $v = \sqrt{v_{\text{rain}}^2 + v_x^2} > v_{\text{rain}}$, giving the impression of moving faster.

Note that in the case of stationary rain, the windshield (that is, the vehicle) moves at the same speed \vec{v} with respect to the rain, where $v_{\text{rain}} = v_y$ represents the speed component at which the windshield moves. In this context, let A_{ws} be the area of the windshield and θ be the angle between the vector indicating vehicle motion and the normal (unit) vector \vec{n} to the windshield, to simply obtain its cross section as $A_{ws} \cos(\theta)$. Typically, the number of raindrops hitting the windshield per second is expressed as $\rho \vec{v} \cdot \vec{\alpha} = \rho(v_x \alpha_x + v_y \alpha_y)$, where ρ is the density of the raindrops and $\vec{\alpha} = A_{ws} \vec{n}$ is the area vector of the windshield.

This simplified model shows that the number of raindrops hitting the windshield increases when driving faster, that is, when v_x (the only variable term) increases. Obviously, in a real scenario, things can be more difficult to model. For example, driving with an increase v_x in the presence of wind, but not faster and in the same direction as the wind, would mitigate the intensity of raindrops hitting the windshield. However, when speed increases, the layer of water on the windshield becomes thicker and more

distorted, thus reducing visibility [5]. According to [19], the speed of the vehicle V plays an even more important role in the reduction of visibility than the thickness of the water film, and this reduction is even more severe when there is the coexistence of raindrops and water spray, in addition to spray alone. This was determined by looking at the safe speed against inadequate visibility, which was determined by examining the sight distance at the stop distance.

2.1.3. Wiper Frequency. Rain significantly affects visibility through a vehicle's windshield, even when windshield wipers are in use. This issue is particularly relevant in the context of intelligent vehicles. Rainwater splashing on the windshield intermittently obscures visibility, acting as a lens that scatters light and distorts the visual representation of the scene [20]. Additionally, debris and movement caused by rain further contribute to reduced visibility and obscure road objects. While windshield wipers are designed to clear the windshield, they are not always completely effective and often leave a thin film of water behind. Moreover, the wipers only clear a portion of the visual field for a limited time, depending on the intensity of the rain.

Spray is also a potentially deadly hazard induced by rain, and it happens when rainfall is pushed up off the road by passing vehicles. Spray can quickly cover the windscreen, drastically reducing sight to near-zero levels. This issue becomes even more crucial in the context of intelligent cars. While larger vehicles such as lorries and buses produce more spray, even a regular-sized family car equipped with clever features and moving at a moderate pace might produce enough spray to be dangerous. When spray hits the windscreen in these conditions, it virtually blinds the driver until the intelligent vehicle's advanced technologies operate to clear the scene. As a result, in the context of intelligent cars, correct prediction of local visibility, including the influence of spray, becomes critical for assuring the safety and performance of these vehicles, especially in severe weather situations. Rain-sensing wipers, for example, are a standard feature on many current vehicles. These wipers detect rain on the windscreen and alter their speed appropriately, ensuring maximum vision for the driver. Furthermore, intelligent headlamp systems, such as adaptive headlights, may modify their angle and intensity depending on the weather conditions, including rain. This improves vision and reduces the danger of accidents by better illuminating the road ahead.

2.1.4. Depth. Estimating the depth of field (DoF) while driving is of great use to the driver, forward-looking depth information plays a crucial role in the ADAS/AD system [21]. A comprehensive and accurate approach to estimating the depth of a traffic incident can effectively ensure road safety. For example, driving in darkness makes it more difficult to judge the distance between incoming vehicles, which is dangerous. As autonomous and self-driving cars become more prevalent, the need for accurate depth perception increases. Accurate depth data aid in gaining a better picture of the situation and making rapid and safe

judgements. Existing approaches, such as lidar, radar, and monocular cameras, present obstacles. Charles Wheatstone proposed stereopsis in 1838 as a sense of three-dimensional objects. This meant that two eyes experienced the same image from different angles and distances in the horizontal plane. This generates horizontal disparity depth indications, also known as binocular disparity. This phenomenon was widely used for experimental purposes. When coupled with chromatically opposing 2D coloured glasses, anaglyphs were used to achieve stereoscopic 3D effects (usually, red and cyan). Recently, powerful algorithms have been employed to extract depth from two images using stereopsis. Two or more image sensors make up a stereo camera. This allows the camera to simulate human binocular vision and sense of depth.

2.1.5. Time of Day and Time Series. The time of day in the rain is especially dangerous at night, with fatalities occurring at rates higher than those of driving at night [22]. The key factors that make driving at night especially dangerous are reduced visibility and substantially longer visual reaction time under reduced light [23]. For the visual perception of the environment lying down, a foundation for scene reconstruction and interpretation with a focus on detection conditions in the forward field at night is particularly important for understanding how the visual system works under nighttime driving conditions in the rain [24]; furthermore, information such as the sequential time series at which the driver is driving under low visibility conditions is critical both in daytime and especially in nighttime conditions where contrast and DoF are lower. Moreover, rain on the windshield also accumulates over a series of time, and this is crucial in the prediction of rain over time that will reduce the visibility based on the factors aforementioned in the properties of rain and the contrast of the scene in the field of view.

2.2. Scene Interpretation and Reconstruction in Autonomous Vehicles. Camera sensors in intelligent and smart cars play an important part in ADAS and AD functionalities. These sensors are used in a variety of components, including perception and visualisation, to allow for scene interpretation, object detection, and tracking, moreover scene reconstruction. They can be used in all three components of the rain visibility estimation function as shown in Figure 1. The perception components of the ADAS/AD functions, which use monocular [25] or camera surround view or stereo vision, can be used to interpret the scene by detecting objects and their distances. In the visualisation components of the ADAS/AD functions, a full 3D reconstruction of the scene from multiple camera views is usually necessary [26]. In effect, to achieve scene reconstruction, 3D models from a set of 2D images need to be built. Surround-view (SV) systems have played an important role in scene reconstruction [27]. Using several camera sensors, a 360-degree field depth of field of the vehicle's surrounding can be extracted by combining those 2D images into a 360-degree 3D view [28, 29].

A depth map is used to separate foreground objects from detected background objects. Then, the distance of each detected object from the centre point of the front camera was computed using monocular geometry or stereo-vision-based techniques [30]. When using more than one camera sensor, depth can be calculated from stereo photogrammetry measurements by triangulating image points from the camera's central point [31]. When only a single camera sensor is available, the problem of depth estimation becomes more difficult. In this scenario, the geometry features of the shapes extracted from the scene should be used for online camera calibration algorithms [32]. Self-supervised monocular depth estimation methods have previously been implemented that exhibit good performance results [33].

It is worth highlighting that scene interpretation and reconstruction become more difficult during motion [34]. To maintain an accurate representation of the extracted objects list, a dynamic algorithm should be implemented taking into account vehicle motion when computing depth maps and objects' distances and coordinates [35]. Odometry is used to estimate vehicle motion from visual input [36]. Typically, in odometry algorithms, different geometrical scene characteristics are extracted and then tracked between consecutive frames in combination with vehicle speed data and camera calibration data for the estimation of ego motion [37].

In the context of scene interpretation using camera sensors, tracking and detection are fundamental processes for understanding and analysing the objects present in the scene [38]. These processes enable the identification, tracking, and estimation of the positions, movements, and characteristics of the objects captured by the cameras.

Detection refers to the initial step of identifying objects in the scene. It involves applying computer vision algorithms and techniques to analyse the camera images and detect the presence of objects such as vehicles, pedestrians, traffic signs, and other relevant entities. Object detection algorithms, such as deep learning-based approaches (e.g., convolutional neural networks), are commonly employed to achieve accurate and robust detection results.

Once objects are detected, the tracking process comes into play. Tracking involves following objects over time, and continuously estimating their positions, velocities, and other relevant attributes. Tracking algorithms use object detection information from consecutive frames to establish object trajectories, associate detections across frames, handle occlusions, and predict future object locations. Multiple object tracking algorithms can employ techniques such as Kalman filters, particle filters, or deep learning-based methods to maintain accurate and consistent object tracks [39].

By combining detection and tracking, the system can create a comprehensive understanding of the scene dynamics and the behaviour of individual objects. This information is crucial for decision-making processes in autonomous vehicles, such as collision avoidance, path planning, and interaction with the environment [40].

In the aforementioned context, the camera sensors (whether monocular, surround view, or stereo vision) provide the necessary visual input for both detection and

tracking algorithms. These algorithms analyse the camera images, extract features, compare them across frames, and use motion models to estimate the positions and movements of the objects. The utilisation of multiple camera sensors allows for a more comprehensive and accurate understanding of the scene, as it provides different viewpoints and perspectives that can improve detection and tracking performance.

Tracking and detection using camera sensors can simulate the driver's visibility and perception from inside the car during rainy conditions. By analysing the camera images captured through the windshield, the system can identify and track objects, enabling it to make informed decisions based on the same visual cues that a driver would rely on. This enhances the safety and performance of autonomous vehicles in adverse weather, replicating the driver's ability to perceive and respond to the environment.

2.3. Hardware-Based Sensors for Scene Interpretation and Reconstruction in Autonomous Driving. The integration of visibility estimation into intelligent cars involves analysing the effects of rain on headlights, windshields, road surfaces, and road markers. These factors impact the efficiency of light sources, create backscatter and glare, and affect the overall contrast and visibility of objects on the road as mentioned in Section 2. By understanding these effects, intelligent cars can adjust their perception algorithms and adapt their driving behaviour to ensure safety.

The perception sensors can be classified into two main types: passive and active. Passive sensors solely capture the energy emitted by the surroundings and generate output signals accordingly. This category includes monocular cameras, stereo cameras, omnidirectional cameras, event cameras, and infrared cameras. On the other hand, active sensors emit energy and gauge the response from the environment. They measure a portion of the reflected energy, enabling them to gather data. Examples of active sensors are LiDAR, radar, and ultrasonic signals [41]. While both perception and visibility play critical roles in ADAS operation during rainy conditions, it is important to differentiate between the two concepts. Perception involves the accurate interpretation of sensor data by the ADAS system, enabling it to understand the surrounding environment. Perception relies on the inputs from various sensors and their ability to detect objects, recognises road markings, and assesses potential hazards. On the other hand, visibility primarily concerns the driver's direct view and the physical barriers that can arise due to rain, such as water accumulating on the windshield, as shown in Figure 2.

Multiple hardware-based sensors are necessary for autonomous vehicles to acquire a reliable ADAS model for the interpretation and reconstruction of the surrounding environment. These include the following:

- (i) RGB, i.e., monocular, stereo vision, or near-infrared (NIR) camera sensors
- (ii) Ultrasonic proximity (US) sensors
- (iii) Global position system (GPS) sensor

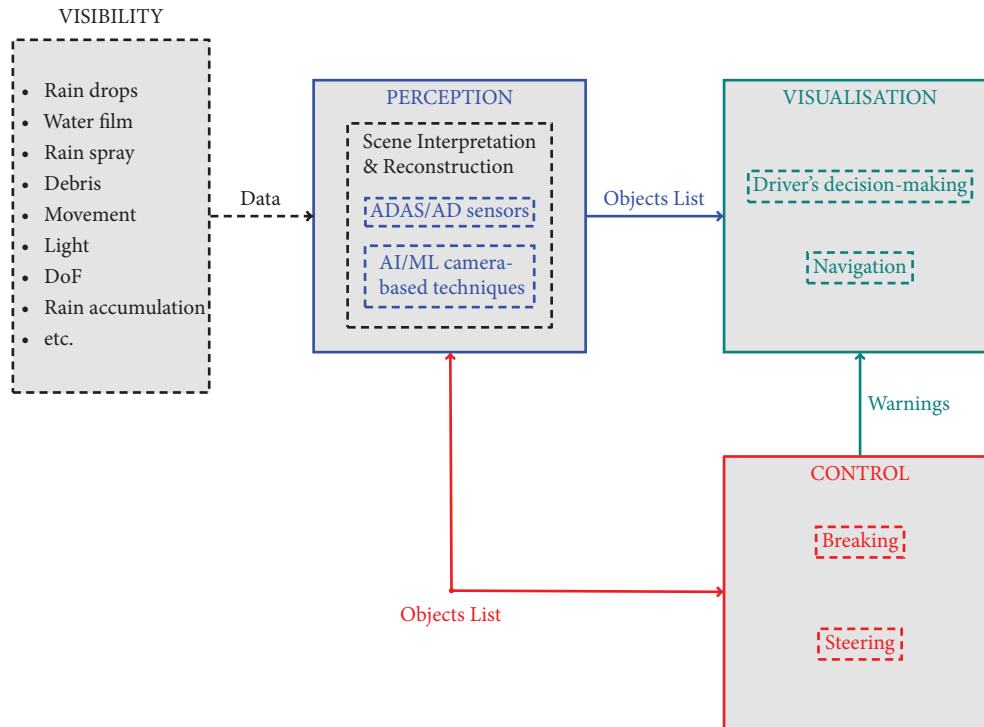


FIGURE 2: ADAS/AD components of the rain visibility estimation function.

(iv) Radio detection and ranging (RADAR) sensor

(v) Light detection and ranging (LIDAR) sensor

The NIR sensors installed in the environment operate in the wavelength range of 780 nm – 3 mm to detect the distance of objects up to 4 m in the scene. Their operation is based on the time-of-flight (ToF) principle and the phase difference between the transmitted and received light pulses. Often, when used in poor lighting conditions, it can offer advantages in detecting objects in comparison to the RGB visible light camera sensors. In addition to NIR sensors, stereo-vision cameras also play a crucial role in perception tasks. By utilising multiple cameras, stereo-vision systems capture depth information and enhance the understanding of the surrounding environment. This depth perception allows for more accurate object detection, tracking, and scene understanding. Here, increasing the number of sensors adds to the computational and overall costs of an ADAS/AD function. Therefore, we propose the use of combined hardware-based sensors only as necessary, rather than as a baseline.

In autonomous vehicles, USs are responsible for detecting objects, in solid, liquid, granular, or other forms, by transmitting sonic waves from 40 kHz to 70 kHz [42]. The US does not get affected by scattering effects when transmitting and receiving back the sonic waves. However, the composition of the air, the temperature, or the noisy road scenes could affect their performance. USs have a limited detection range of objects of no more than 2 m and limited angular sensing resolution. Therefore, their performance in

detecting the location of objects and the velocity of vehicles can be inconsistent.

The RADAR sensor uses radio waves for object detection. When transmitted waves are reflected back by an object on its path, the RADAR antenna collects the returned signal, and the TOF principle is applied to calculate the precise distance of the object and its velocity with respect to the location of the RADAR. The operational wavelengths of RADAR can range from 24 GHz to 79 GHz for autonomous vehicles and are classified as short-, medium-, and long-range detection. RADAR systems can be used to improve the safety of autonomous vehicles [43] and integrate them into ADAS/AD functions such as cross-traffic warning, adaptive cruise control, blind spot detection, collision avoidance systems, and others.

LIDAR sensors use the TOF principle for a pulse of infrared, or NIR, light from a laser diode. LIDAR operational waves are commonly in the range of 905 – 1550 nm. Their performance problems are mainly due to interference from their mechanical scanning system and other light sources. Most modern LIDAR systems offer a detection range of 200 – 300 m [42].

GPS-based sensors are used for various localisation systems. Their performance may suffer when the satellite signal is lost. GPS sensors are often used in combination with inertia measurement units (IMU) to also measure the angular rate and orientation of the autonomous vehicle. Combined GPS and IMU solutions play a key role in various visualisation, control, and perception components of ADAS/AD functions [44].

3. Sensor Performance Software for Deraining: Enhancing Perception, Visualisation, and Control

Rain-induced distortions present considerable challenges to the performance of sensor technologies used in ADAS. Cameras, LiDAR, and radar systems encounter difficulties in tasks such as segmentation, tracking, and object detection due to adverse weather conditions, particularly rain. Addressing these challenges is crucial to ensuring the safety and reliability of ADAS technologies under rain and other weather conditions leading to poor visibility. It is worth noting that rain-induced visibility issues can also impact the clarity of windshields. Currently, many fully autonomous vehicles are working on deraining methods to address this problem. However, semiautonomous vehicles, where the driver remains involved, have not received adequate attention when operating in heavy rain conditions. The adaptation of ADAS for fully autonomous and semi-autonomous vehicles is a persistent concern, and the integration of ML and deep learning (DL) approaches into deraining algorithms is emerging as a promising solution to mitigate these challenges [45].

Both supervised and unsupervised learning can be used to train these algorithms to identify and remove rain-related artefacts from sensor data, thus enhancing perception by eliminating rain-induced interference. DL architectures, such as convolutional neural networks (CNNs) and generative adversarial networks (GANs), can further improve the visual representation of the road environment by enhancing the clarity and reliability of sensor data. A good example of a DL system for deraining and image restoration is “Transweather” [46], which employs transformer-based image restoration techniques, and others can be found in the comprehensive review on data-driven single image deraining in [47]. As for the visualisation component, systems such as “Weatherstream” [48] and the work on learning weather-specific and weather-general characteristics for image restoration in [49] provide further insight on improving visual clarity under adverse weather conditions.

In this context, sensor fusion is becoming important to augment the effectiveness of deraining algorithms. Through the amalgamation of data from various sensor types, such as cameras, LiDAR, and radars, ADAS can gain a more comprehensive understanding of the environment. This approach mitigates the adverse effects of rain on individual sensors and ultimately improves the accuracy of decision-making processes. Despite advances, significant challenges persist, particularly when heavy rain complicates visibility for vision-based ADAS. A classic example involves windshield wipers that remove raindrops that distort images captured by frontal view cameras in the vehicle. However, this removal simultaneously causes occlusion, potentially obstructing visibility, and further complicating the situation. A mitigation system for occlusion is discussed in [50].

We emphasise that real-time performance is of paramount importance for deraining algorithms to be truly effective in ADAS. Swift processing and correction of sensor data are essential to enable timely responses to dynamic road

and weather conditions. Efficient software design plays a pivotal role in ensuring real-time operation, empowering these algorithms to significantly improve ADAS performance in rainy conditions. Figure 3 illustrates how a deraining pipeline should be integrated with an ADAS system to benefit all its components and graphically reports the implication of embedding deraining algorithms in autonomous or semiautonomous vehicles.

Figure 3 delineates a multifaceted system adapted for semiautonomous vehicles, demonstrating the integration of a deraining pipeline with ADAS. Here, the perception block is responsible for the initial processing of sensory data, including the derivation of a rain map and the generation of cleared images, thus mitigating rain-induced distortions and interference. The visualisation block focuses on enhancing the interface between the system and the human driver, employing augmented reality tools, and facilitating seamless transitions to manual control. The control block, in turn, embodies the decision-making functionalities of the system, analysing the impact of deraining algorithms and determining appropriate vehicular responses. Interconnections between these blocks ensure a smooth flow of information, allowing for real-time adaptation to rain conditions.

4. Categorisation

In this section, we survey the existing literature and categorise it based on different methodologies and models. Furthermore, we analyse them and extract key aspects from each considered study to provide a detailed overview, also displayed in schematic tables, thus summarising relevant concepts and allowing comparative analysis across the study. Figure 4 shows the combined articles surveyed on a chromatic and timeline basis. The timeline from left to right shows chronological increases, showing the article’s publishing year and the names of the corresponding authors. The chromatic analysis follows Figure 1 and Figure 2, i.e., perception and control-based articles that were surveyed have been chromatically indicated, and the same applies to the perception and visualisation and the visualisation and control surveyed articles, also.

4.1. Real-Time Frame-Based Methodologies. Real-time frame-based methodologies for rain visibility estimation solutions mainly involve the perception and control components of ADAS/AD functions in autonomous vehicles. As camera sensor-based solutions do not suffer from deterioration due to scattering effects or due to precipitation in atmospheric conditions, these sensors are not limited in their detection range from the TOF operational principle and are inexpensive, offering an overall more reliable and cost-effective solution for developing a rain visibility estimation system. For the purpose of this categorisation, we group all such solutions under the category of real-time frame-based methodologies. Modern camera-based ADAS/AD functions can offer a near-human-like scene interpretation [24].

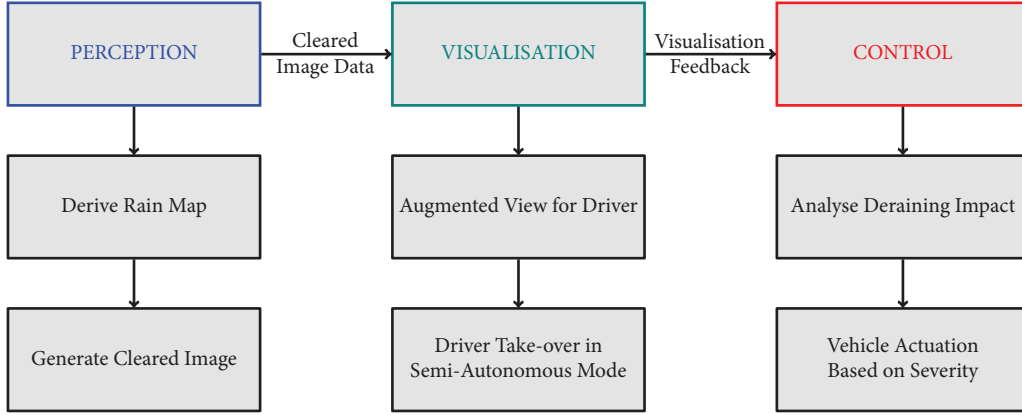


FIGURE 3: A deraining pipeline integrated with perception, visualisation, and control components and its implications for semiautonomous vehicles.

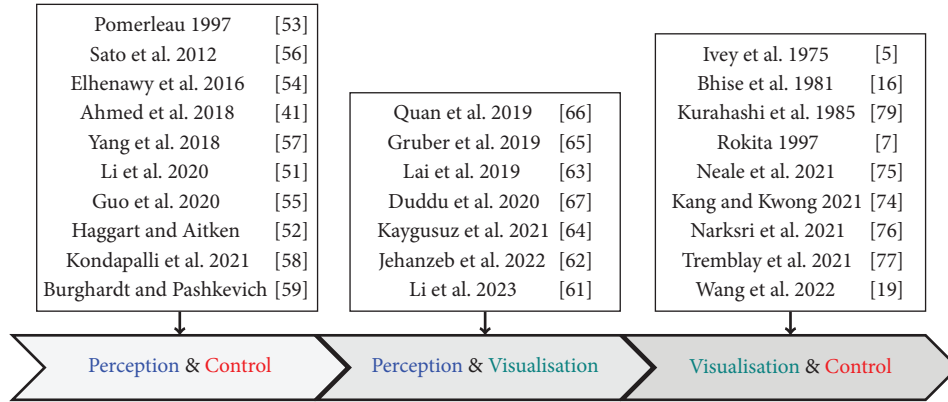


FIGURE 4: Combined timeline-based and chromatic-based surveyed articles.

The authors of [51] apply optical flow estimation to understand and interpret rainy scenes caused by rain streaks and rain accumulation. Their method combines both the residue channel and the coloured residue image channel, which are correspondingly free from rain streaks and rain accumulation. To further improve the performance of their proposed algorithm, they applied an optimisation technique based on an objective function and piecewise smooth structure layers. Their optimisation technique consists of layer separation and optical flow computation steps. Assume that the exposure time is T and that the elapsed time, while a raindrop passes through a pixel x , is τ . $I = (I_r, I_g, I_b)^T$ is the colour vector representing the intensity of the colour. $L = (L_r, L_g, L_b)^T$ is the colour vector of the light brightness. $B = (B_r, B_g, B_b)^T$ is the colour vector of the background reflection. ρ_{rs} consists of the refraction, specular reflections, and internal coefficients of a raindrop. Then, the following normalisation step to the input image $I(x)$ is defined as follows:

$$I(x) = I_{rs}i + I_{bg}, \quad (1)$$

where $i = (1, 1, 1)^T$, $I_{rs} = \tau\rho_{rs}L$, and $I_{bg} = (T - \tau)B/\sigma$. The vector division is performed element-wise. Thus, the vector residue channel can be defined as follows:

$$I_{res} = I^M - I^m, \quad (2)$$

where $I^M = \max\{I_r, I_g, I_b\}$ and $I^m = \min\{I_r, I_g, I_b\}$. I_{res} is called the residue channel of image I and is free of rain streaks. To evaluate the performance of the proposed optical flow method for scene interpretation, the authors first conducted an ablation study in which gradually more rain streaks were placed to increase the levels of rain accumulation. Then, three different types of dataset were tested as follows:

- (i) Images in which synthetic rain was added to them
- (ii) Images which combined real rain with synthesised object motions and
- (iii) Images which consisted of real rain and real motion, too

This approach outperforms other state-of-the-art algorithms over the three datasets under investigation.

An improved simultaneous localisation and mapping (SLAM) method, based on the indirect visual SLAM technique ORB-SLAM2, is proposed in [52]. In ORB-SLAM2, the extracted binary features are tracked between frames for a consistent position estimation. Thus, the proposed ORB-SLAM2 SVE model is able to take into account light

scattering in the atmosphere to estimate dynamic visibility distances based on the presence of fog. The extracted characteristics are taken from the observed contrast of the road markings. This model provides robust performances when tested over various driving conditions, including fog and glare caused by sunlight.

The work in [53] describes and assesses a real-time vision system for identifying and tracking automobiles on roads when visibility is decreased due to rain or other weather circumstances. This solution uses a forward-looking video camera mounted on the front of a moving car to calculate the distance between the car and other cars on the road. The authors describe findings from studies conducted on picture sequences under adverse visibility circumstances. Visibility is measured using the range of the most distant object on the road that has at least 5% contrast using a car equipped with an onboard camera. Instead, a transferable model is introduced in [54] using speed probe data and associated weather and visibility data. This concept is applicable to any length of road. The method is based on the assumption that traffic conditions can be divided into three regimes: congestion, speed at capacity, and free flow. Additionally, the speed distribution is made up of three parts. The mean of each part is determined using linear regression, with various weather conditions and visibility levels serving as predictors. An in-vehicle camera is introduced that detects both the sky and the road, and the results conclude that when visibility increases, so does the speed of the driver. Furthermore, it is the first to be able to automatically identify congestion. The authors of [41] examine perception sensors installed on a mobile platform for real-time visibility estimation in off-road environments. The study highlights the challenges of obstacle recognition in dense vegetation using LiDAR point clouds and emphasises the need for advanced data processing and higher-resolution scanners. Vision sensors, such as cameras, also face difficulties in recognising objects hidden behind vegetation. In [55], the camera characteristics are combined to calculate the visual distance of the input frame. The vehicle-mounted camera mimicked the shooting and recording of the front scene in the experiment, while the vehicle-mounted radar measured and recorded the distance, relative speed, and angle of the barriers and vehicles in front of the experimental vehicle. In this study, anthropic visibility is defined as the period in which camera and radar captured data were synchronised with vehicle distance assessed by millimetre wave radar at the point of loss of tracking. Humanistic visibility is measured in the same way that human eyes do, and visibility detection using an in-vehicle camera and millimetre wave (mm-W) radar, and weather conditions and visibility predictors are provided. The resulting algorithm achieves results similar to those of human eyes, with an accuracy of 88%, 91%, 90%, and 95% to operate with no taillight and the vehicle clearance lamp, emergency flasher, and fog lamp, respectively.

In [56], an image-processing approach is used to evaluate the visibility of traffic lights for drivers in wet weather. It generates visual noise that matches the visual properties of human eyes and was used to estimate the visibility of traffic lights for drivers. Visual noise is quantified by counting the

quantity and size of raindrops on the windshield, then integrating visual noise and texture data to evaluate the visibility of traffic signals to drivers. An experiment using photos from the vehicle camera demonstrated that, unlike previous techniques, the new method is capable of properly estimating the visibility of traffic signals for vehicles in wet weather conditions. These algorithms calculate two characteristics: the number of raindrops detected on the windshield, called I_r , and the average size of the raindrops, called I_s . The value of each characteristic was determined by the following equation:

$$I_r = N_{\text{rain}},$$

$$I_s = \frac{1}{N_{\text{rain}}} \sum_{i=0}^{N_{\text{rain}}} S_i, \quad (3)$$

where S_i is the area of the raindrop i^{th} and N_{rain} is the number of raindrops. The visibility of a traffic light is proportional to the degree of textural contrast between the signal and its surroundings. Therefore, by operating in the frequency domain, the suggested technique assesses the textural difference between a traffic signal and its surroundings and uses it to compute visibility. The proposed method surrounds a traffic signal with three-by-three blocks. Here, the width and height of the traffic signal are W and H , respectively, and the i^{th} block is represented as $f_i (i = 0, 1, \dots, 8)$. Then, the pixel values in each block are converted into the (spacial) frequency domain through the fast Fourier transform (FFT), which produces the power spectrum $F_i(j, k)$ of each block. Subsequently, the texture difference between the traffic signal and its surroundings is calculated as the following equation:

$$I_t = \sum_{i=0}^8 \sum_{j=0}^W \sum_{k=0}^H |F_0(j, k) - F_i(j, k)|. \quad (4)$$

Finally, with linear regression, the features of visual noise and texture difference are combined and derived, and a visibility equation is set as follows:

$$\hat{V} = \sum_{n=1}^N \lambda_n I_n, \quad (5)$$

where N is the number of features to estimate visibility, i_n is the n^{th} feature calculated by applying the method described above, and λ_n is the weight of the n^{th} feature.

The authors of [57] propose two image processing techniques, i.e., enhanced dark channel prior (DCP) and weighted image entropy (WIE), as well as a support vector machine (SVM) classifier to provide a real-time visibility indicator. Results show a 25% accuracy enhancement over other estimation techniques, and the speed of the proposed model is also faster by 26% than other conventional DCP methods.

The authors of [58] propose an algorithm for rain detection and severity classification to use in vision-based systems of autonomous driving scenarios. The algorithm is based on a neural network that takes localised discrete cosine transform

(DCT) and image-based features as input. The algorithm is tested on a real dataset and subjectively quantified with respect to the severity of the rain. The authors performed experiments in multiple settings to obtain the optimal configuration consisting of a DCT window size of 32×32 and 10 DCT coefficients. This returns the best possible accuracy of 99.9%, outperforming the state-of-the-art algorithms in terms of accuracy. In terms of complexity, it also requires significantly less memory. In fact, current state-of-the-art algorithms require up to 80% more memory usage. The proposed algorithm is suitable for the implementation of the classification of road severity of rain for autonomous vehicles.

The authors of [59] assess the brightness of the road markings and the pavement of the nearby road, to calculate the so-called “Weber” contrast. The study shows that the average contrast ratio on typical roads is 0.8 during the day and 2.0 at night. These values are significantly enhanced by digital image modification, resulting in an increase of 2.3 and 6.8, respectively. In low-light conditions (glare or rain interference), the average contrast ratio drops to 0.5 (improved to 1.4); in the worst-case scenario, it drops below 0.1. As a result, the authors conclude that current machine vision technologies may fail in low-light circumstances. However, image enhancement appears to substantially increase both the original and digitally enhanced contrast ratios for machine vision equipment.

Key details of this analysis are reported in Table 1 for comparison between studies.

4.2. Deep Learning. DL methodologies for rain visibility estimation are mainly integrated into the perception and visualisation components of the ADAS/AD functions in autonomous vehicles.

The study in [61] presents a technique to assess the robustness of visual perception systems to demanding weather events using generated meta-datasets. The authors study the elements affecting the resilience of the visual perception system, establish a physics-based weather production model for rainy and foggy settings, and provide measurable meta-datasets with visibility in fog and rain intensity as changeable parameters. The researchers then used regression analysis and statistical testing to assess the resilience of object recognition systems in the face of more demanding weather frames. This technique allows for a quantitative evaluation of the dependability of AI devices using predetermined performance measures.

In [62], the authors propose a deep learning system that features a domain-incremental mechanism through statistical correction. This is obtained with a simple online zero-forgetting strategy that can progressively learn new scenarios, such as rain, without the need for retraining or costly memory banks. Their technique provides a physics-based rain model to simulate photorealistic rain at 8 different levels of severity, and targets such as cars, pedestrians, and cyclists are observed.

In [63], a deep convolutional neural network (CNN) is used to measure visibility whether a wiper is needed, and a pretrained “ResNet” model is used for rain detection. The

day experiments yielded a precision result of 64.4%, while the night experiment yielded a precision of 53.5%.

The authors of [64] propose a novel deep sensor fusion framework that estimates vehicle movement using pose and uncertainty estimations from multiple cameras onboard. The deep learning models employed do not require manually selected scene features due to their ability to learn meaningful feature representations using the input scene images. Precisely, a hybrid CNN-recurrent neural network (RNN) architecture is used for the extraction of spatio-temporal features from images. Instead, a mixture density network (MDN) is used to predict the probability distributions of motion for each camera. In this study, a total of 6 cameras are considered in the vehicle in the nuScenes dataset (which included images in different weather and lighting conditions, such as daylight, rain, and night). The results show that the 6-camera fused deep learning model performs better than individual camera-based estimates by incorporating complementary information from different points of view. Compared to other state-of-the-art methods using the same dataset, the performance of other SLAM-based methods decreases in rain and at night, while the proposed method maintains its accurate trajectories’ predictions under all weather and lighting conditions.

Similarly, the authors of [65] apply the evaluation methodology using pixel accuracy depth evaluation (PA-DE) in four characteristic automotive scenarios recorded in varying weather conditions, using the naturalistic driving study dataset. The results show that current stereo approaches provide significantly more stable depth estimates than monocular methods and LIDAR completion in adverse weather. Meanwhile, the authors of [66] adopt CNNs to remove the effect of raindrops from the image. The approach exploits shape-driven attention and outperforms commonly accepted methods in terms of both quantitative metrics and visual quality.

The authors of [66] propose a CNN-based method for removing raindrops from a single image. The authors introduce a double attention mechanism that takes advantage of shape-driven attention and channel recalibration. The shape-driven attention module uses physical shape priors of raindrops, such as convexness and contour closedness, to accurately locate raindrop regions. The channel recalibration module improves the robustness when processing raindrops with varying appearances. The proposed CNN outperforms the state-of-the-art approaches in terms of both quantitative metrics and visual quality.

The authors of [67] use a backpropagation neural network (BPNN) applied to meteorological data from 238 weather monitoring stations to predict rain and fog conditions on the link road. They have achieved comparable accuracy.

Table 2 provides an overview of deep learning methods.

4.3. Simulation. Many simulations in the past had been conducted using field tests and observational studies to deduce the visibility approximation. However, recent

TABLE 1: Summary of the analysis of real-time visibility estimation methods or image processing.

Article	Year	Methodology	Model	Dataset	Results/accuracy
[59]	2022	Road markings and neighbouring road luminance and determination of the Weber contrast	GNU IMP	In-vehicle camera, 1080 × 1920, 140° (dataset unavailable)	X
[58]	2021	Rain detection and severity classification algorithm based on a neural network uses localised DCT and image-based features	CNN with DCT	(Available from author) in-vehicle camera 1,07,309 frames	Testing accuracy is 94.84%, and validation is 98.97%
[52]	2021	SLAM and light scattering with dynamic visibility distance	ORB-SLAM2 SVE	Cam, SV, IMU, GPS, LMS	Outperforms ORB-SLAM2 under (a) foggy and (b) glare caused by sunlight
[55]	2020	Visibility detection via weather conditions and visibility predictors	Adaboost and DSST	In-vehicle camera, mm-wave radar (dataset unavailable)	88% with no taillights, 91% with clearance lamps, 90% with emergency flashers and 95% with fog lamp
[51]	2018	Layer separation and optical flow computation	Real-time optical flow	(Available at [60])	Better performance than state-of-the-art methods
[41]	2018	Distinguishing objects against the background in the operational environment	YOLO v5	Daylight camera, thermal camera, 60°FOV (dataset unavailable)	YoloV5 is not applicable in unstructured environments
[57]	2018	Image processing-improved DCP and WIE	Real-time SVM	Road-side units (dataset unavailable)	25% more accurate and 26% faster than DCP
[54]	2016	Classification in 3 traffic states: "congestion," "speed at capacity," and "free flow"	Linear regression	Geographic, speed, traffic message channel (dataset unavailable)	Congestion identification considering weather condition and visibility
[56]	2012	Use of two visual noise features affecting the visibility of signals	Image processing methods integrating visual noise in image texture features	29, 600 × 375 images in-vehicle camera (dataset unavailable)	MAE = 0.137 SD = 0.085
[53]	1997	Measuring attention contrast between road features ahead of the vehicle	Ralph vision systems use visibility distance of target detection	120 images (dataset unavailable)	Better performances than traditional methods in various conditions

TABLE 2: Summary of analysis on deep learning-based visibility estimation methods.

Article	Year	Methodology	Model	Dataset	Results/accuracy
[61]	2023	Evaluate the robustness of the object detection model under different weather variations. Meta-dataset statistics help to evaluate visual perception algorithms and forecast their rain and fog performance Zero-forgetting approach which can incrementally learn new tasks (i.e., rain) without requiring retraining or expensive memory banks	YOLOv3, SSD Faster-RCNN, DetectoRS CenterNet, FSAF, FCOS swin transformer PVT, PVTv2	KITTI [68] and CityScape [69]	Mean average precision (order of models): 0.82, 0.808, 0.901, 0.891, 0.6459 0.882, 0.868, 0.92 0.881, and 0.887
[62]	2022	Zero-forgetting approach which can incrementally learn new tasks (i.e., rain) without requiring retraining or expensive memory banks	YOLOv3 (DISC with CNN) disjoint model	KITTI [68]	Mean average precision (@ 50 Hz) rain DISC model 73.9 disjoint CNN model 88.5
[64]	2021	Spatio-temporal features with multicamera prediction of probability mixture density network (MDN)	MC-fusion (CNN-RNN)	6-DoF cameras nuScenes dataset (available at [70])	Day (RMSE, Max, Mean, std) (0.04, 0.15, 0.03, ± 0.02) rain (RMSE, Max, Mean, std) (0.04, 0.14, 0.03, ± 0.03) night (RMSE, Max, Mean, std) (0.07, 0.26, 0.05, ± 0.04)
[67]	2020	BPNN for rain visibility prediction	CNN	Meteorological stations (available at [71])	X
[63]		Time-series, CNN for wiper visibility activation	ResNet	Camera/150 k windshield images (dataset unavailable)	94% daytime 79.2% nighttime
[65]	2019	Evaluation methodology in four characteristic automotive scenarios	PA-DE	Stereo camera, lidar (available at [72])	Higher stability and lidar completion than monocular methods in rain
[66]		CNN for raindrops removal (it uses shape-driven attention exploits)	CNN	Camera (available at [73])	Outperforms the state-of-the-art quantitatively, metrics-wise, and in visual quality

advances in computer vision are driven by models with great capacity trained on enormous datasets.

The authors of [5] consider several factors that can contribute to a reduction in visibility in their simulation, namely, vehicle speed, rainfall intensity, and wiper frequency, among other factors that are less investigated, such as colour and size of the subject, distance to the subject, illumination, droplet distribution of water size, and windshield clarity, to conclude that rainfall intensity is the main factor in reducing visibility. Furthermore, if the windshield wiper rate is on a low setting, they suggest that visibility from inside a vehicle S_V can be modelled as shown in the following equation:

$$S_V = \frac{K}{I^n} \left(\frac{V_K}{V_i} \right)^a \left(\frac{W_i}{W_K} \right)^b, \quad (6)$$

where I^n models the rain intensity, K is some constant dictated by the objective, V_i is any speed for which visibility is to be computed, and V_K is the speed at which the constant K is determined. Similarly, W_i is the cyclic rate of the wipers, and W_K is the cyclic rate of the wiper when K is empirically determined.

The authors of [7] use adaptive iterative image filtering, this article provides an effective approach to display the visual effects induced by rain on the windshield, having the benefit of being simply implemented in a pipeline. Extensions based on the suggested technique may be introduced as the final steps of the visualisation pipeline to current rendering systems. The proposed technique can be used to generate realistic effects in real time in a variety of applications, including a visibility simulator.

Similarly, in [16], the authors studied the visibility of the target cars from a distance during natural rains. The observers were mounted on a vehicle and were alerted when they identified a target vehicle when their wipers were active or had just stopped. These trials show that detection distances drop dramatically with ambient light and that visibility distances decrease with increasing rain intensity. The visibility distance for observers onboard a moving vehicle (versus stationary) is found to be shorter as a result of the higher concentration of water on the windscreen. A model for the visibility distance of vehicles through the windshield is defined in rainy and sunny conditions, based on these tests, with the simplified formulation expressed in the following equation:

$$D = c_0 (r_t)^{-c_1} e^{-c_2 L_b}, \quad (7)$$

where c_0 , c_1 , and c_2 are strictly positive constants, r_t denotes the accumulation of rainwater on the windshield (that is, r is the intensity of the rain and t is the duration between wiper operations), and L_b denotes the ambient brightness. The authors of [74] developed a model to evaluate the effectiveness of a driver visibility system in the presence of rain at night. The system is composed of two components: a laboratory system in which calibrated rain can be generated to imitate rain on a car's windshield in a dark tunnel with regulated lighting and a field system in which calibrated rain

can be created to replicate rain on a field. The second component of the methodology is an experimental procedure. Two visual tasks were chosen, one that involved danger recognition (target detection) and the other that involved reading traffic signs (word vs. non-word discrimination).

In [75], the authors establish a technique to simulate the impact of rain on driver vision by analysing and modelling real video footage taken in dry and rainy settings, during the day and at night. Baseline raw video footage that is not affected by rain is monitored, and using projection mapping and rain modelling, this baseline film is generated to accurately depict the impact of rain on driver vision. The strategy presented in this article employs video projection mapping techniques to construct a virtual environment based on video. Because the lighting, texture, and material properties of the computer environment can be controlled and altered, the simulated world can be customised to visually match the rain conditions. This technique simulates heavy, moderate, or light rain by altering the properties of the reflections, refraction, and lighting of the materials. Compared to the actual video footage, the contrast and lighting factors are fairly realistic.

The authors of [76] evaluated visibility using 3D point clouds and road network maps. The proposed technique overlays depth images with lane locations from a road network map and a 3D scan of the driving environment from a point cloud map. These images are compared to identify visible and obscured areas of the driving environment. The visibility ratio, a numerical number that encapsulates visibility information for a specific area, is also suggested. The visibility ratio is obtained by dividing the viewable area by the driving area. The suggested technique was evaluated in both simulated and real-world driving scenarios. Furthermore, the test findings reveal that the visibility ratio reflects the real visibility of certain sites.

The authors of [77] present a rain rendering pipeline that allows for the evaluation of computer vision algorithms under controlled amounts of rain. Three different methods are presented to add synthetic rain to existing image datasets: completely physics-based, completely data-driven, and a combination of both. The rendered rain is validated with a user study and found to be 73% more realistic than the state-of-the-art. The study shows that the performance of object detection, semantic segmentation, and depth estimation algorithms decreases in degraded weather, on the order of 15%, 60%, and a 6-fold increase in depth estimation error. However, fine-tuning of the synthetic augmented data results in improvements of 21% in object detection, 37% in semantic segmentation, and 8% in depth estimation. It can be observed that object detection and depth estimation capacity is reduced with higher intensity in rain, plus performance decreases when raindrops block the view or fog-like limits the visibility in the image.

The authors of [19] investigate how precipitation impairs visibility, thereby increasing the probability of traffic accidents. It presents a numerical simulation method for analysing the degree to which the coupling of spray and raindrops reduces visibility and suggests safe speeds in the event of poor

visibility. Using real highway design parameters and rainfall conditions, the study models the spray-raindrop coupling particles. This study estimates the visibility of the road by simulating the multiple scattering of taillights in a spray-rain medium. It calculates the maximum safe speed when visibility is poor by comparing visibility with the required stopping sight distance. The results indicate that a high front-mounted truck speed or a thick water film significantly reduces road visibility and the maximum safe speed of the ego vehicle. Additionally, the study indicates that the speed of the front vehicle has a greater impact on visibility reduction than the thickness of the water film. The authors then provide a quantitative examination of the relationship between visibility, precipitation, and vehicle speed. It suggests that reducing the speed of the lead vehicle can significantly improve road visibility and suggests safe speeds to prevent traffic accidents in the event of inadequate visibility.

Table 3 provides a comprehensive overview of the aforementioned simulation methods.

5. Comparison

This section entails the comparison of the models based on their methods of estimating visibility by evaluating all the physical factors contributing to reduced visibility mentioned in Section 2, we then critically analyse how they can be integrated into ADAS components such as; Perception and Control, Perception and Visualisation, and finally Visualisation and Control. Figure 3 shows the combined timeline-based and chromatic-based surveyed articles that we used in 4 and now in this section.

5.1. Perception and Control. Real-time visibility estimation in ADAS is a crucial process that requires the coordinated operation of both the perception and control components. The perception component uses a variety of sensors such as cameras, Lidars, and radars to gather data about the environment and the vehicle's surroundings. These data are then processed and analysed using sophisticated algorithms to extract valuable information, such as object detection, lane detection, and obstacle recognition. The resulting information is passed on to the control component, which uses it to assist the driver in making safe and informed driving decisions. This section reviews real-time techniques with respect to their potential integration in the perception and control component.

[51] uses a robust optical flow in rainy scenes for the purpose of visibility improvement under intense rain conditions, and in low-contrast scenes, a residue channel is applied to detect the rain using a high-frequency layer, a charge-coupled device (CCD) is used to get the darkness of the image, no exact rain intensity is highlighted, speed and wiper frequency has not been considered, such optical flow optimised models for rainy scenes would be utilised in the perception component of the ADAS/AD functions. The algorithm would be used to generate the list of objects. Then, the list of objects would be used in the control component to train the steering function of the autonomous vehicle.

Similarly with [51] in [52] SLAM models for stereo scene reconstruction would be used in the perception component of the ADAS/AD vehicle functions. The reconstructed stereo scene would be used for extracting the scene objects and, then, for the generation of the object list. The control component would read the object list to train the steering function of the autonomous vehicle.

Similarly to [64], SLAM models for stereo scene reconstruction would be used in the perception component of the ADAS/AD vehicle functions. The reconstructed stereo scene would be used for extracting the scene objects and, then, for the generation of the object list. The control component would read the object list to train the steering function of the autonomous vehicle.

[53] provides an estimate of visibility by measuring the contrast of attention between consistent road characteristics at various distances ahead of the vehicle. Daytime rain, with significant water buildup on the windshield and substantial suspended spray in the air, is approximately 0.2% compared to the normal visibility condition during the daytime driving tested in this study. The disadvantage of this approach is that it gives an absolute estimate of how far ahead a feature or obstacle can be found. Furthermore, it does not give measures of the intensity of the rain. Such real-time vision systems would be used by the perception component of ADAS/AD functions. Distance values extracted from detected road vehicles would be integrated into the generated object list and then fed from the perception component into the control component. The control component would be reading the object list and using it to train the steering and braking functions of the vehicle. A different approach, proposed in [54], proposes this time as an estimate of visibility using speed as a characteristic between 0 – 80 mph, light rain, medium, heavy, and freezing, the model can work day and night and provides precise congestion identification considering the weather condition and visibility in a time series approach. The limitations are first that visibility is not clearly defined and that the depth of the driver is not taken into account. Such a model that combines vehicle speed data and associated weather and visibility data would be used in the perception component of the ADAS/AD functions. The extracted categorisation of traffic conditions, such as congestion, speed at capacity, and free flow, would be included together with the list of objects and passed to the control component. The control component would incorporate traffic categorisation information when training mainly the vehicle break function to optimise it under those traffic conditions. [55] considers heavy rain and uses a visibility range between 150 – 200 m to pose a risk; however, this method can only work for local visibility estimation when the taillights are on and only has a few use cases during the day, for example, if fog is considered. Such algorithms which provide visibility predictors under various weather conditions are used as a parameter in the perception component of the ADAS/AD functions. Then, the computed depth estimates of the detected road objects could be adjusted before producing the object list.

TABLE 3: Summary of the analysis of simulation visibility estimation methods.

Article	Year	Methodology	Model	Results/accuracy
[19]	2022	Simulating taillights dispersion in the spray-rain medium to evaluate road visibility, and calculation of the maximum safe speed based on the stopping sight distance in low visibility	Numerical simulation	Critical visibility at 88, 84, 80, and 77 km/h critical and water-film thickness of 0.5, 1.0, 2.5, and 5 mm
[77]		Rain rendering pipeline for evaluating computer vision algorithms under controlled amounts of rain	KITTI [68] CityScape [69] nuScenes [70]	Fine-tuning improvements +21% object detection, 37% on semantic segmentation, 8% depth estimation
[76]	2021	3D point clouds, road network maps, and a 3D scan of the driving environment	Town01/CARLA (available at [78])	The visibility ratio represents the actual road visibility
[74]		Pedestrian targets in a lab that can simulate rain at night, by comparing contrast ratio (Weber contrast)	Custom facility	Hardware recommendation for sensor-integrated headlamps
[75]		Generating video realistic computer-simulated rain and the effect of the rain it has on driver visibility	Custom simulation	Simulates rain by altering material reflexions, refractions, and lighting
[7]	1997	Adaptive iterative picture filtering	Custom filterer	Produces real-time realistic and optical effects
[79]	1985	(O.T.F.)-based evaluation system	Measurement principle of optical response function (O.T.F.)	Heavy rainfall simulation with max 220 km/hr wind speed and 2 mm/min of rainfall
[16]	1981	Detection of target from stationary and in-motion	Statistical model	Seeing distances range from 9% to 23%
[5]	1975	Observational photographic study	Custom simulation	Variable speed limits for rain at 1 in./hr

In [57], the authors use visibility as a function of the distance from the images between 38 – 358 m. The model includes day and night conditions, as well as rainy conditions and an adaptive speed limit mechanism. However, it does not justify the local visibility in high-intensity rain through the windshield. Such image-processing-based techniques for estimating visibility would be used in the perception component of the ADAS/AD functions. Thus, the computed visibility estimate values would be passed along with the object list to the control component. The control component could then use these values to train the vehicle break function of the vehicle. Similarly to [57] above, in [56] the image processing algorithms will be used in the perception component of the ADAS/AD functions. Thus, the extracted information on the visibility of the traffic lights in rainy conditions would be passed along together with the object list to the control component. The control component could then use that information to train, for example, the collision avoidance braking function. An approach based on measuring the contrast ratio (CR) is proposed in [59], where the CR is compared with the enhanced CR image under day and night conditions, and the speed was evaluated up to 140km/h. However, no speed-based evaluation was present; CR was evaluated under rainy conditions, drizzle, and glare; however, a limitation is that intensity does not appear to be considered, which could reduce the results of using Weber contrast for machine vision technology in higher intensities of rain [56] estimate the visibility of drivers toward traffic lights during rainy conditions, raindrops, and heavy rain during the day. However, this is only applicable to traffic signals and not to other potential hazards; another limitation is that it does not differentiate the colours of traffic lights. Moreover, this has not been tested during nighttime conditions; depth is not considered, so the model does not state how far it can process the traffic lights to prewarn the driver of the colour. Such algorithms to assess the brightness of the scene would be used in the perception component of the ADAS/AD functions. Then, the extracted average contrast ratio values could be used together with the generated objects list and passed into the control component. Then, those values would be used for training the steering function of the vehicle, e.g. in automated parking scenarios.

The authors of [58] propose a solution for visibility based on the severity of the rain. Their system uses images captured from a camera installed in the vehicle and analyses the rain droplets on the sensor screen as well as the overall loss of information (or entropy) caused by the rain. The severity of the rain can be classified on the basis of these two factors. Although the camera is placed inside the vehicle, the frequency of the wiper has not been considered to classify the severity of the rain. Furthermore, it is unclear how the authors classed the initial rain classes as the intensities of rain did not appear to be indicated in the manuscript. Their solution to visibility based on the severity of the rain could help improve the performance of these sensors during rainy conditions. For example, using the vehicle, the autonomous vehicle could detect the severity of the rain and adjust the settings of its cameras to improve their performance in rainy conditions. This could allow the vehicle to better perceive the environment around it and make more accurate decisions,

such as adjusting its speed, changing lanes, or avoiding obstacles on the road. Furthermore, the solution for visibility based on the severity of the rain could also help improve the control of the autonomous vehicle during rainy conditions. By automatically adjusting its speed, trajectory, and other control parameters based on the severity of rain, the vehicle could maintain safe driving conditions and avoid possible accidents. The perception and control of off-road autonomous driving are examined in [41]. Due to uneven terrain, fluctuating sunlight, and the presence of obstacles such as rocks, trees, and flora, off-road settings present special problems for perception systems. To recognise and track objects in these difficult situations, the authors suggest a perception framework that integrates camera pictures and LiDAR point clouds. They emphasise the need for cutting-edge data-processing approaches for reliable perception and draw attention to the shortcomings of current algorithms in accurately interpreting off-road scenes. The article also examines various control modes, including path planning and speed control, and assesses how useful they are in off-road driving situations. To ensure safe and effective operation, the analysis of braking distances also emphasises the integration of perceptual and control components. Research advances the development of intelligent transportation technologies in difficult locations by addressing these elements and providing insightful contributions on perception and control issues unique to ADAS systems working in off-road circumstances.

A summary of the real-time methods is provided in Table 4 with respect to their perception and control components.

5.2. Perception and Visualisation. This section reviews deep learning techniques with respect to their perception and visualisation components. ADAS leverage the combination of perception and visualisation to improve driver safety and awareness. Perception involves using sensors to gather data about the driving environment, such as the vehicle's surroundings, while visualisation presents these data to the driver in a format that is easy to understand and act upon. By using these two technologies together, ADAS can provide drivers with valuable information and alerts to help them make informed driving decisions.

Deep learning techniques can further improve the accuracy and reliability of ADAS by enabling the system to classify objects in the driving environment. With the integration of deep learning techniques, such as CNNs in perception and visualisation technologies, ADAS can.

- (1) Identify potential hazards and other important information;
- (2) Classify them accurately;
- (3) Present information to the driver in an easily understandable format, making it easy to react to them.

Incorporating deraining techniques into ADAS can enhance perception data obtained after deraining and can be utilised to improve both the perception and visualisation components, including the heads-up display (HUD).

TABLE 4: Comparison of real-time frame-based approaches in real time with respect to their perception (P) and control (C) ADAS/AD function components.

Article	Rain		Properties	Vehicle speed	Time series		Time		DoF	WF	Comp	
	Intensity				Day	Night	Day	Night			P	C
[59]	X		X	X	X	✓	✓	2-5 m, 7-9 m, 30-45 m	X	✓	✓	
[58]	Light, medium, heavy (no precise intensity)		Entropy, low frequency	X	✓	✓	X	X	X	✓	✓	
[52]	Rain (no precise intensity)		X	X	✓	X	X	(Specific value used not defined)	✓	X	✓	
[55]	Heavy rain (no precise intensity)		X	X	✓	X	X	150-200 m	X	✓	✓	
[51]	Rain streaks and rain accumulation		Synthesised or real	X	✓	X	X	X	X	✓	✓	
[41]	X		X	0 - 20 mph	✓	✓	✓	✓	X	✓	✓	
[57]	X		X	X	✓	✓	✓	38, 64, 73, 168, 296, 358 (m)	X	✓	✓	
[54]	Light rain, medium, heavy, and freezing (no precise intensity)		X	0 - 80 mph	✓	X	X	—	X	✓	✓	
[56]	Raindrops/heavy (intensity not reported)		X	X	✓	X	X	✓	X	✓	✓	
[53]	Rain (no precise intensity)		Opacity	X	✓	X	✓	700, 400, 300, 100 (m)	X	✓	✓	

Deraining algorithms remove rain streaks and enhance the visibility of captured images or videos, improving the quality and reliability of the perception system. This enhanced perception data, free from unwanted artefacts caused by rain, can provide a clearer and more accurate representation of the driving environment. By idolising this improved perception data, ADAS can better detect and interpret objects, road conditions, and potential hazards, even in rainy conditions.

The derained perception data can then be utilised in the visualisation component, such as the HUD, to present meaningful and actionable information to the driver. The HUD overlays this information onto the driver's line of sight, typically on the windshield or a dedicated display surface, allowing the driver to access critical information without diverting their attention from the road, in vehicles that are not autonomous or have ADAS capability this information is typically displayed on an infotainment display in the vehicle for better visual capability to the driver in dangerous situations such as providing night-vision for detecting pedestrians.

This approach provides drivers with the information they need to make safe driving decisions, thus reducing the risk of accidents and improving overall road safety. The combination of perception, visualisation, and deep learning is then a powerful approach to improving driver safety and awareness.

Hereinafter, we explore these deep learning visibility estimation techniques and evaluate their capabilities along with their potential for integration in their ADAS components.

In [63], images from the perspective of a driver of the entire windshield are trained both for day and night. The intensity of the rain is mentioned; however, the data are collected manually from online sources and are considered to activate the wiper. Therefore, no true intensity of the rain is considered and a time series is given for input after 1.2 s using 6 frames to decide when to activate the wiper. Depth is not considered a function of visibility, nor are contrast and properties of rain. The main limitation is the manual extraction of data, which requires someone to check every frame to determine if it is degraded in visibility, and, seeing as the pattern of heavy rain is finite, you would need to manually class each different image. Information on accuracy calculations under different conditions, daytime and nighttime, would be incorporated into the perception component when reconstructing the scene and used by the ADAS/AD functions. Furthermore, the visualisation component would incorporate accurate information to assist in driver decision-making and road navigation.

The authors of [61] employ AI-based visual perception systems and test them in severe weather conditions to assess their resilience. The main focus is on the components that affect the visual perception system's resilience and the design of a weather-generating model for rainy and foggy settings. The model creates realistic visual data that meet difficult weather formation. The authors create synthetic meta-datasets to test sophisticated algorithms under more difficult weather conditions. Regression analysis and statistical

testing confirm the nonlinear link between model performance and weather variation. The research covers the need to analyse and test AI-based visual perception systems in severe weather conditions for ADAS. Indeed, it simplifies data collection for the evaluation of the robustness of the visual perception system, and it improves operational AI dependability. This study shows an interaction with ADAS' perception and visualisation components by evaluating the resilience of AI-based visual perception systems in diverse weather circumstances, thus making ADAS more reliable and safer in adverse weather conditions. Unfortunately, the authors did not specify how they captured the intensities of the rain and the relationship between the speed of the car and the rain properties. This is a big limitation in terms of replicability as these may change when considering a windshield of a vehicle and the realism may also be different from the physical rain simulator.

In [62], the authors develop a more robust object detection system for autonomous vehicles by using camera pictures taken from the KITTI dataset. Its objective is to adapt to changes in the environment, such as heavy rain, and it offers information on the key changes in performance to detect various types of weather under varying rain intensities. This work is heavily based on level 5 autonomous vehicles; however, with the incrementally learned history of the data, this can be used in semiautonomous vehicles by the perception component; the authors could adapt this model to use the perception and pass it to the visualisation component to enable the driver to comprehend the upcoming risks in heavy rain or other adverse weather conditions.

In [64], camera-based visual odometry approaches to estimate vehicle trajectories under various road conditions would be implemented in the perception component of the ADAS/AD functions to generate the object list. Then, the generated objects list would be utilised in the steering function of the control component. Furthermore, the visualisation component could read the predicted trajectories of the vehicle and assist the vehicle's navigation by visualising the information to the driver.

[65] takes a different approach based on the stereo vision to capture the depth in metres, from 0 to 100 m, and also considers light and heavy rain, i.e. with intensity in the range 15 – 55 mm/h/m², with images taken both during the day and at night. A limitation of this study is that it does not provide visibility from inside the vehicle, as the cameras are outside; the cyclic frequency and wiper are not considered along with the windshield and speed of the vehicle, which can affect depth accuracy. These stereo depth estimates improve the object list generated by the perception component of the ADAS/AD functions. Additionally, more stable depth estimates would be used in the visualisation component to improve driver navigation decision-making in adverse conditions such as rain, fog, or snow. [66] adopts a CNN to remove the effect of raindrops in images and takes advantage of shape-driven attention. This approach outperforms established methods in terms of both quantitative metrics and visual quality. This technique would not affect the objects list generated by the perception component, but instead would be used for the visualisation component of the

ADAS/AD functions by assisting in the stitched-up surround view scene using the camera sensors. Meanwhile, the authors of [67] predict visibility at the level of the road link, considering the intensity of the rain up to 101 and 120 mm/h, the size of the drop, and physical properties such as geometric scattering. However, this model can only be used for specific regions and states and cannot provide a local visibility estimate from the driver's perspective. As for [66], this technique would be used mainly for the visualisation component of ADAS/AD functions by incorporating the predicted conditions to inform the driver.

Table 5 provides an overview of the comparison of deep learning approaches with respect to their perception and visualisation components.

5.3. Visualisation and Control. The combination of visualisation and control components works in tandem with simulated methods for estimating visibility. These simulated methods allow researchers to study visibility in a controlled and safe manner, without the risk of real-world accidents. The visualisation component in ADAS plays a crucial role in providing a visual representation of the data collected by the perception component. The control component in ADAS is responsible for utilising the data gathered by the perception component to make real-time decisions that improve driver safety. It integrates with the visualisation component to provide a comprehensive understanding of the virtual environment and to inform the driver of potential hazards or risks. If the perception component detects an obstacle in the vehicle's path, the control component can use the visualisation component to provide the driver with a visual representation of the obstacle and suggest a course of action, such as slowing down or changing lanes. Simulated methods for estimating visibility in ADAS allow researchers to test and evaluate the effectiveness of various visibility-enhancing solutions and technologies in a controlled environment. By integrating perception, visualisation, and control components, these simulated methods provide a comprehensive understanding of the virtual environment and enable researchers to make informed decisions that enhance driver safety. Ultimately, the combination of simulated methods for estimating visibility with the visualisation and control components of ADAS has the potential to improve road safety and reduce accidents caused by low visibility. This section then evaluates how the simulation techniques could be concerning their visualisation and control components.

The work in [5] conducts a field test based on reviewing photographs and obtaining visibility, developing an approximate equation for driver visibility that depends on the intensity of rain, the speed of the vehicle, and the cyclic frequency of windshield wipers. Traffic speeds above 45 mph are shown to be unsafe when passing manoeuvres are performed during the rainfall of 1 in. In one hour, the observed visibility of the driver was 30% in 60 mph and 3.9 in./h and in 30 mph with 48 cycles and 15% with 35 cycles. This simulation is used to generate the control component model, as shown above 7, in the ADAS/AD functions. Furthermore, the simulated behaviour of the observer distance learned from the trials during ambient

light and intense rain can be used in the visualisation component to assist in the decision-making of the driver's road navigation. Thus, the visualisation component would adjust the visually shown stitched-up surround view scene to match the actual distances between the vehicle and the road objects.

The field test in [16] provides drivers with a button to press when they can detect a target object. In most cases, they neglected the vehicle speed beyond 64 – 72 km/h because they felt that the windshields could become very saturated at that point, and their vision distance prediction was based on similar characteristics that combine rain intensity, rain accumulation time, and ambient daylight. In addition to this, the contrast of the target vehicle concerning the background is treated as a random variable. This contrast could explain some of the variability in the seeing distances. Furthermore, the intensity from light rain to heavy rain is found to be equivalent from 1 cycle per minute to 45 cycles per minute. This is a limitation, as the intensity of the rain is only captured every 10 minutes, which may not work for the estimation of local visibility in real time. This visibility model can be used in the control component of the ADAS/AD functions, as well as in the visualisation component. In the control component, the visibility distance D (of equation (7)) could be used to estimate the behaviour of vehicle failure in heavy rain conditions and integrated in the visualisation component for drivers to see. This would help them make decisions while driving the vehicle.

In another field test, as described in [79], a simulation is carried out with 57 cpm and heavy rain of 1 mm/pm. The intensity of the rain is used here as a parameter, as is the wiper frequency, to further improve the estimate of the visibility of the driver. A strong focus is given to different regions in the driver area of the windshield to conclude that the wind speed with the intensity of the heavy rain reduces visibility. A similar approach is adopted in [7], where an image processing approach is used to simulate raindrops on a windshield with both drops and film being considered to estimate visibility. Such simulations are used in the visualisation component of the ADAS/AD functions by incorporating those generated realistic visual effects of rain when informing the driver about the driving conditions.

Instead, the study in [76] aims to calculate a visibility ratio (0 – 1) for a particular area. Depth is also taken into account using a road network map. The visibility ratio can be used mainly in the control component of the ADAS/AD functions. Therefore, the visibility ratio value could be used to estimate the steering and braking behaviour of the vehicle in these different driving environments. A limitation of this method is that rain and other weather conditions can cause degradation, which, as mentioned by the authors, could be potentially solved with data fusion. Another limitation is that it is not clear whether the model works at night. For a night-based approach to estimating visibility, one can consider the work in [74], focusing on the intensity of the rain in 20 and 50 mm/h, corresponding to heavy and violent rain at various distances from 5 – 25 m of the target. Contrast is also considered using black and white targets, and in this study, two colour temperatures of 3000 k and

TABLE 5: Comparison of deep learning approaches with respect to their perception (P) and visualisation (V) ADAS/AD function components.

Article	Rain		Properties	Vehicle speed	Time		DoF	WF	Component			
	Intensity	Rain			Day	Night			P	V		
[61]	Light to heavy storm 0 mm/hr to 200 mm/hr	Raindrop size distribution volume, and lens angle Table 6, [77]	X	X	✓	X	✓	X	✓	✓		
[62]	Light to heavy rain 1 mm/hr to 200 mm/hr				✓	X			✓	✓		
[64]	Light and heavy rain (subjective definition)	X	X	0-63 km	✓	X	X	1.25 HZ (max)	✓	✓		
[67]	Precipitation levels (in the presence of 1.6 km)	X	X	X	✓	✓	✓	X	✓	✓		
[63]	Light and heavy rain (subjective definition)	Puddles, streaks, and raindrops	X	X	✓	✓	✓	1.25 HZ (max)	✓	✓		
[65]	15 - 55 mm/h/m ²				✓	✓	✓	✓	✓	X	✓	✓
[66]	Raindrops				Convexness, nonanisotropy, and contour closedness	X	X	✓	X	X	X	✓

TABLE 6: Comparison of simulation visibility estimation methods with respect to their visualisation (V) and control (C) ADAS/AD function components.

Article	Rain		Properties	Vehicle speed	Time series		Time		DoF	WF	Components	
	Intensity				Day	Night	V	C				
[19]	3.125 (mm/min)		Film thickness, raindrop size, and scattering of photons	70, 90, 120 (km/h)	X	X	X	X	X	X	✓	✓
[77]	Moderate, heavy, shower 50, 100, 200 (mm/h)		Position and dynamics of all raindrops greater than 1 mm	0, 100 (km/h)	✓	✓	✓	✓	✓	✓	✓	✓
[76]	No precise intensity		X	X	X	X	X	X	X	X	✓	✓
[74]	Heavy, violent 20 and 50 (mm/h)		X	X	X	X	X	X	X	X	✓	✓
[75]	Light (0.0 to 0.1in/h), moderate (0.11 – 0.29in/h), and heavy (≥0.30in/h)		Contrast, reflection, and droplets	–	X	✓	✓	5, 12.5, 25 (m)	X	X	✓	✓
[7]	Raindrops only, water film (no precise intensity)		Hydrodynamics	X	X	–	–	X	X	X	✓	✓
[79]	0.2 to 150 mm/h and droplets' velocity from 1 to 8 m/s		Colour, brightness contrast, and atmospheric attenuation	50 km/h and 130km/h	✓	✓	✓	X	X	✓ No cycles given	✓	✓
[16]	0 – 38mm/h (no precise intensity)		Contrast, brightness, and thickness	64km/h	✓	✓	✓	1.3, 3.2km/h	45cpm	✓	✓	✓
[5]	0 to 4.00in/hr			0 to 80km/h	✓	✓	✓	X	X	X	✓	✓

6000k are selected. A limitation of this approach is that the measurements do not take into account the rain that accumulates on the windshield, and the cyclic frequency of the windshield is also not considered to account for local visibility. These simulations could be used mainly in the visualisation component of the ADAS/AD functions to display appropriate visual warnings to the driver to assist them in making decisions while driving in rainy conditions. In [75], both day and night conditions are considered, where visibility in rain conditions is simulated using an in-vehicle camera and a simulated environment using Nuke for projection mapping. Furthermore, there are also factors that influence visibility based on contrast, reflections, lighting, colour particles in the air, and rain intensity, such as light (0.0to0.1 in/h), moderate (0.11 – 0.29 in/h), and heavy (0.30 in/h or more), which are taken into account. Some limitations of this study include the lack of data with a water film on the windshield, and that the visibility ratio has not been defined based on their simulated model. The model could be used to simulate visibility estimation; however, the data are limited and difficult to acquire. In addition, it does not seem to show the correlation of the simulated environment with the wiper and the cyclic frequency. The study in [77] quantitatively assesses a simulation of rain based on the performance of object detection and depth estimation. In this system, the control component could take data from the perception component, and the outputs of the object detection and depth estimation systems can be fed to the visualisation component to warn the driver of dangerous visibility conditions. A limitation of this work is that speed is not mapped to the intensity of the rain. Therefore, the relative velocity is not taken into account and cannot be used to assess the drivers' visibility through the windshield. The thickness of the water film is considered in [19], where other factors are also investigated, such as the generation of sprays, the distribution of raindrop size, and the spray-raindrop coupling particle, which were separately introduced together with the process of multiple scattering of light photons. These factors are all used in the proposed visibility estimation method. The study also relates visibility with speed. However, a limitation of the empirical approach is that the time of day is never considered to estimate visibility. The same can be said for the frequency of the wiper, which is also a factor that would affect the results of the spray on the windshield.

Table 6 shows a comparison of the simulation techniques discussed concerning their control and visualisation components.

6. Conclusion

We offer a comprehensive review of visibility estimation approaches in rain condensation on the windshield, including milestone works and the most modern approaches forming the state-of-the-art. Both data-driven and model-driven approaches are analysed. The current state-of-the-art solutions in rain visibility estimation used to

reconstruct the driver's view for object detection-based autonomous driving are too surveyed and categorised into (1) real-time frame-based methods, (2) deep learning methods, and (3) simulation methods. For each category, we highlight key aspects relating to their perception components, their control components, and their visualisation components of the ADAS/AD function. In this light, this work is unique and makes it possible for researchers and practitioners in the field to easily compare different methods and find pros and cons, thus providing future research and/or the selection of the best approach for a given situation. On the basis of this work, we can draw the following conclusions:

- (1) Camera sensor-based solutions do not suffer from deterioration due to scattering effects or due to precipitation under atmospheric conditions. They are not limited in their detection range from the ToF operational principle and are inexpensive, offering an overall more reliable and cost-effective solution for developing a rain visibility estimation system. In contrast to LIDAR, lithium systems have a limited effective range because the backscattered optical signal weakens with the target range, so returns from very distant targets are too weak for the photo-receiver to detect.
- (2) Interpretation and reconstruction of scenes are keys to robust ADAS/AD vehicle functions. From the scene interpretation and reconstruction, the extracted objects list can be generated. However, that object list can be affected by adverse weather conditions. The object list is passed from the perception component into the control component and is also read by the visualisation component.
- (3) Real-time frame-based methods and models that combine vehicle speed data and associated weather and visibility data seem to be the most effective to implement by the perception component of the ADAS/AD functions. Such models would be used in the generation of the object list to be incorporated into the control component for vehicle breakdown and steering functions.
- (4) Deep learning approaches seem to have the greatest impact when they can provide a visibility predictor under various conditions of rain and adverse conditions. Such predictors are used as a parameter in the perception component of the ADAS/AD functions. They can adjust and improve the accuracy of the depth estimates of detected road objects while generating the object list.
- (5) Simulation-based techniques and models play mainly a role in the visualisation component of the ADAS/AD functions. They can be used to generate warnings and other visual indications that can assist the driver in making decisions and navigating the vehicle. Less could be used in the control component, where, for example, the visibility distance D

extracted from the simulation models is used to improve vehicle braking behaviour under heavy rain conditions.

7. Future Work

In all types of weather and road conditions, visibility is an essential element of driving activity. As described previously, the generation of an appropriate objects list is necessary and key for any ADAS/AD function. Camera sensors are used by most ADAS/AD autonomous vehicles for this purpose. Therefore, scene interpretation and reconstruction have a significant impact on the performance of these ADAS/AD vehicle functions and can be affected by rain conditions. Therefore, it becomes clear that camera sensors-based rain visibility estimation solutions are the most promising to focus future research efforts.

Additionally, real-time frame-based solutions for scene interpretation and reconstruction that combine vehicle speed data and associated weather and visibility data appear to be most effective when implemented by the perception component of the ADAS/AD vehicle functions.

Deep learning approaches to understanding the scene can have the greatest impact when providing a visibility predictor in various adverse conditions of rain. Rain visibility estimation with inexpensive camera sensors implemented in the perception component of the ADAS/AD functions is expected to become increasingly popular in commercially available autonomous vehicles in the automotive industry. Adding modern deep learning models to improve performance is surely a promising approach that should be further investigated in the future. Moreover, by utilising the perception component of ADAS, we can determine the quality of visibility, which can be measured using the aforementioned inputs in the tables, and these factors contributing to reduced visibility can be sought out from camera sensors to determine a threshold for dangerous driving under multiple rain intensities which can, in turn, pass the controls to the control component, and then, visualisation for the driver can also be an optional addition for safety systems to help assist the driver when these conditions are met.

By combining this local drivers' visibility information with the intelligent vehicle's internal sensors and navigation systems, intelligent vehicles can make informed decisions and adapt their behaviour accordingly. For example, if the local visibility is significantly reduced due to rain, the vehicle can automatically adjust its speed, activate specific lighting systems, or even communicate with nearby vehicles to ensure safe driving.

Finally, integrating local drivers' visibility information with broader transportation infrastructure, such as weather monitoring systems and traffic management centres, can enable intelligent vehicles to send real-time updates about visibility conditions along their routes and pass them on to other drivers in the area. This integration can enhance the vehicle's ability to proactively respond to changing visibility conditions and improve overall safety on the road.

Data Availability

We submit a survey article which requires no primary data. We included comments on the availability of datasets of the surveyed studies in our article.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Authors' Contributions

Jarrad Neil Morden investigated the study, visualised the study, wrote the original draft, contributed to conceptualisation, and reviewed and edited the study. Fabio Caraffini performed supervision, contributed to visualisation, wrote the original draft, contributed to conceptualisation, and reviewed and edited the study. Ioannis Kypraios performed visualisation, wrote the original draft, and reviewed and edited the study. Ali H. Al-Bayatti performed supervision, contributed to conceptualisation, and reviewed and edited the study. Richard Smith performed supervision.

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