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ANALYSIS OF SENSORS FOR AUTONOMOUS VEHICLES DEVELOPMENT

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Abstract

The automobile industry has undergone a transformation with the introduction of autonomous cars, which hold the promise of safer, more efficient, and convenient transportation in the future. With its promise of improved safety, efficiency, and convenience, autonomous cars represent a revolutionary paradigm change in the automobile industry. These vehicles' ability to sense and comprehend their surroundings is largely dependent on their advanced sensor suite. The objective of this thesis is to present a comprehensive study of the sensors that are essential for autonomous cars, assessing their technological complexities, advantages, drawbacks, and integration difficulties. The research also explores the comparison between human drivers and autonomous vehicles sensors. We have proposed an efficient algorithm to mitigate the existing sensor systems. In principle, the study would offer a comprehensive investigation of autonomous vehicle sensors and acknowledge complex relationships between risks variables, software, hardware, or decision-making processes. In this study, a brief discussion will be made of the future scope for implementing the findings of the research.

1 Introduction

Self-driving automobiles, or autonomous vehicles, are a fast-emerging technology that has the potential to completely change how we travel [1]. For navigation, obstacle avoidance, and decision-making, these vehicles use sensors, cameras, and machine learning algorithms [2] [3]. They are safer and more effective than conventional cars as they don't require human involvement to operate [4]. Road safety, traffic flow, and the number of accidents brought on by human mistakes might all be enhanced by autonomous cars. They can also improve the freedom and quality of life of those who are unable to drive, such as the elderly and those with impairments, by giving them more mobility. Nevertheless, there are obstacles related to their implementation, such as technological, legal, and social problems.

The history of autonomous cars begins with Siegfried Marcus's creation of the first automobile in 1870 [1]. The notion of remote directing a vehicle dates back to 1898, which is when the idea of turning conventional automobiles into autonomous vehicles first emerged [2]. Electronic guidance systems and automated gear changes are two examples of the autonomous characteristics that have been developed throughout time as a result of technological improvements [3] [4]. Modern automobiles now frequently come equipped with semi-autonomous functions like adaptive cruise control, automated braking, and lane keeping [5]. The majority of automakers are expected to introduce completely autonomous vehicles before the turn of the century, with the future of autonomous vehicles being vast networks of vision-guided systems. The advancement of AI algorithms and sophisticated processing technology has been crucial in improving autonomous driving capabilities.

In 2018, there were 1.35 million road traffic deaths globally, making it the eighth most prevalent cause of accidental death for people of all ages, according to the World Health Organization's (WHO) Global Status Report. [5] There are still over 40,000 traffic deaths in the European Union (EU) per year, 90% of which are due to human error, despite a decline in the number of registered deaths. Because of this, foreign investors have made significant investments to improve traffic flow and aid in the development of self-driving automobiles. Furthermore, by reducing the quantity of carbon emissions, autonomous vehicles (AVs) are expected to support efforts to reduce carbon emissions. [6]

In this paper, the functions of sensors utilized in autonomous cars will be briefly examined. Specific sensor types will be explored along with their benefits and drawbacks. The present hardware and software conditions will be taken into account, and several techniques for risk factor evaluation of these sensors will be highlighted. Based on the criteria, generic and dynamic risks will be mentioned. Lastly, a discussion of how autonomous car sensors make decisions that are comparable to that of a human driver will be addressed.

2 Literature Review

2.1 History

The development of self-driving technology began in the middle of the 20th century, which is when autonomous cars first appeared on the scene. The Navlab project at Carnegie Mellon University successfully showed an autonomous vehicle that could navigate real-world surroundings in the 1980s, which brought significant attention to the subject. Autonomous vehicle research was driven in the ensuing decades by developments in artificial intelligence, processing power, and sensor technology. The race towards autonomy accelerated in the 2000s with the start of large-scale programmes by businesses like Google that thoroughly tested self-driving cars. The first state in the union to permit the use of driverless cars on public roads was Nevada in 2012. Subsequently, significant automakers and IT firms have ventured into the domain of autonomous vehicles, carrying out extensive testing and implementing partially autonomous functionalities.

A Precedence Research report puts the size of the global AV market at over 6500 units in 2019 and projects a compound annual growth rate of 63.5% between 2020 and 2027 [7]. In 2009, Google started developing a self-driving car project behind closed doors. Currently known as Waymo, the project is a part of Alphabet, Google's parent company. In 2014, Waymo presented a completely autonomous car prototype that lacked a pedal board and steering wheel [8]. With 25 cities throughout the United States of America (USA), Waymo's autonomous vehicles have now covered more than 20 million miles on public roads, marking an impressive accomplishment [9]. According to Jaguar Land Rover (JLR) Ireland, testing of its next-generation autonomous cars will take place over 450 km of roads in Ireland in 2020.

JLR Ireland will collaborate with Shannon, Ireland's autonomous car center [10]. The narrative around autonomous cars in the twenty-first century is being shaped by the constant evolution of legislative frameworks, technical advancements, and public acceptance.

2.2 Functional schematics of Autonomous Vehicles

The interactions between an AV's numerous hardware and software components that enable it to do its purpose are shown in its functional architecture [11]. AV's hardware includes sensors, actuators, and linked automobiles. The three components are perception, planning, and controlling. Figure 1 shows the functional architecture of an AV.

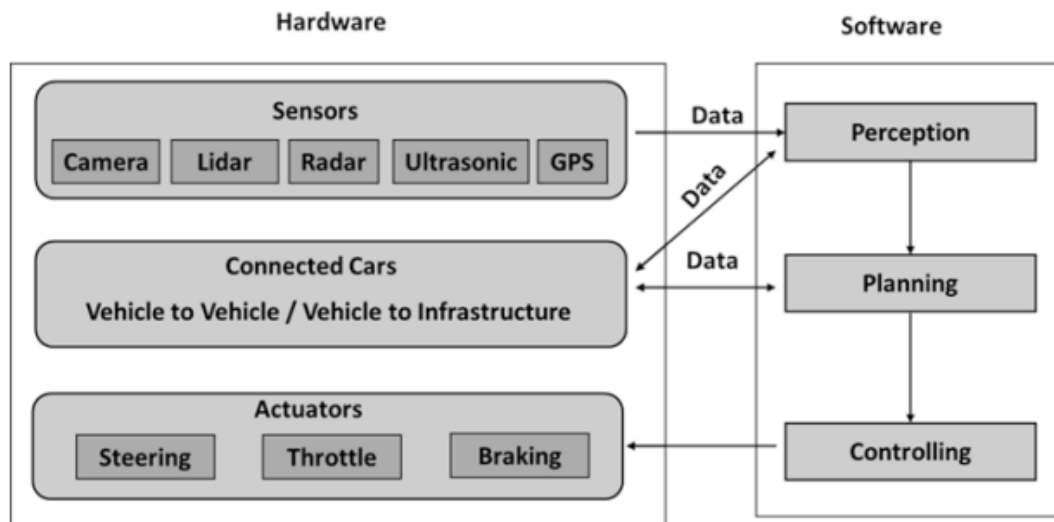


Figure 1. Functional schematics of AV [11]

In addition to supporting high-precision maps and the Internet of Vehicles, the autonomous system consists of decision, perception, and control layers. Among them, a variety of hardware sensors in the perception layer record the vehicle's location and data about the surrounding environment. The on-board sensors that are now in use include millimeter-wave radar, LiDAR, and cameras.

The decision layer models the environment, creates global knowledge, makes decisions and judgements, and transmits the signal instructions for vehicle execution based on the input data from the perception layer. Ultimately, the control layer transforms the decision layer's signal into the vehicle's action behavior [12].

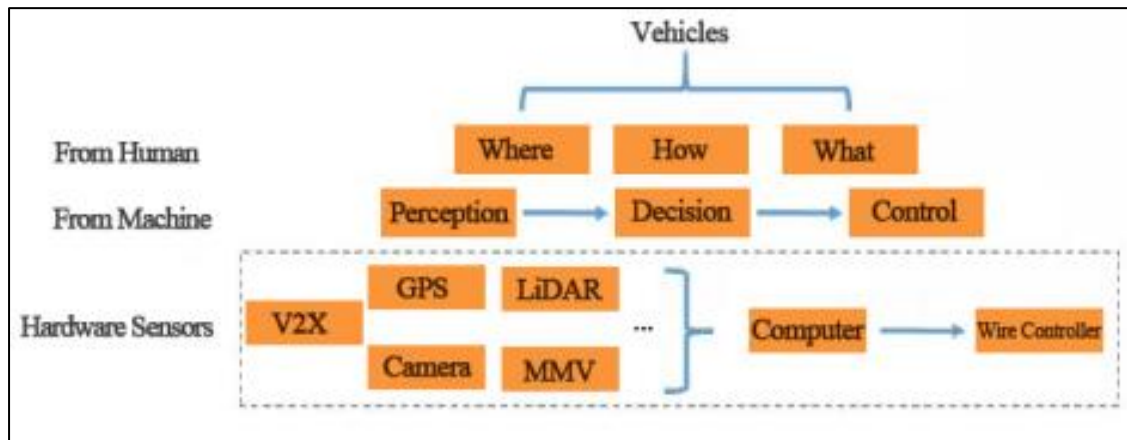


Figure 2. System Schematic of AV[13]

3 Sensors in Autonomous Vehicles

Sensors are devices that transform perceived events or environmental changes into measurable measurements that may be further analyzed. The two categories of sensors are based on the way they work. Autonomous vehicles need sensors in order to detect their surroundings well. These vehicles are equipped with many highly redundant perceptive sensors to ensure reliability and safety in any driving condition. However, the pillars of any autonomous system, sensor synchronization and calibration, are made more difficult by multi-sensor systems, such as radar, LiDAR, and camera systems [14]. Ensuring that the sensors listed above operate with the least amount of mistake and accidents will be necessary to improve safety sensors in autonomous cars.

The placements, coverage, and applications of environment perception sensors in typical AV applications are shown in Figure 3. The exact and correct detection of objects, together with the individual and relative placement of many sensors, are critical for the safe and dependable execution of any subsequent activities [15]. It is typically challenging to generate enough information in AV from a single, independent source. The advantages of the three primary sensors—radars, LiDARs, and cameras—used in AV applications to sense their surroundings are discussed in this section. In addition to the applications the sensors make possible, the LiDAR coverage is shown by red regions, the camera coverage is shown by grey areas, the

short- and medium-range radar coverage is shown by blue areas, and the long-range radar coverage is shown by green areas.

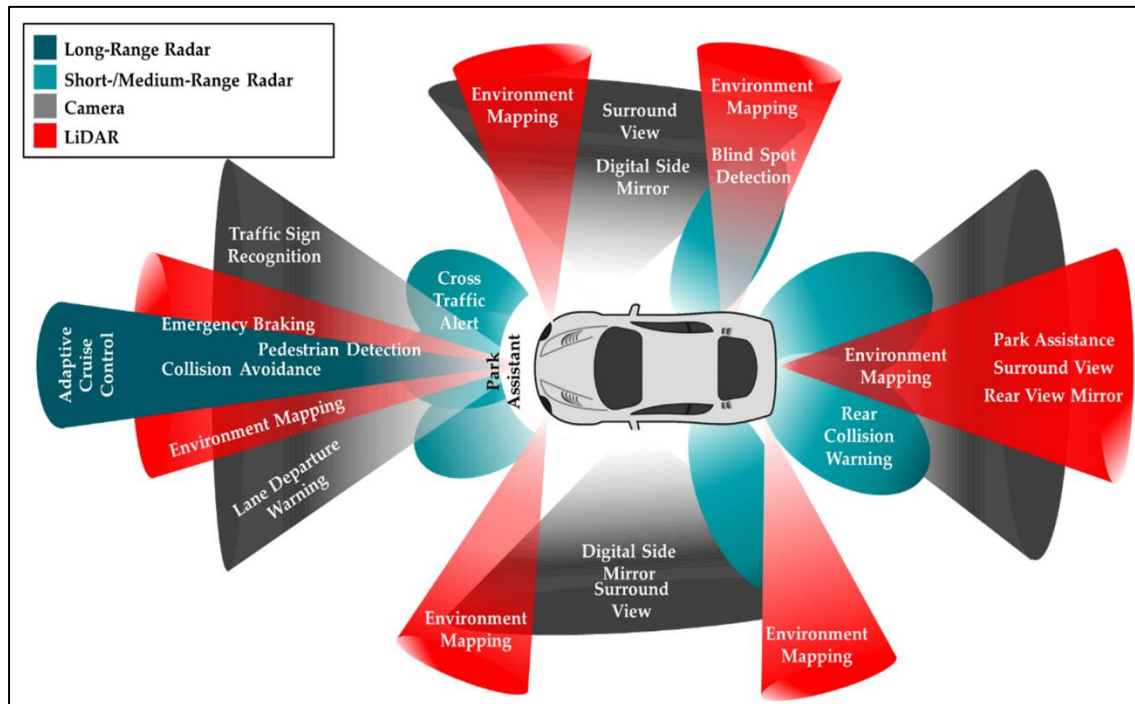


Figure 3. An illustration of the kind and arrangement of sensors in an autonomous car that allow the car to sense its surroundings. [16]

3.1 Camera

Cameras are highly helpful for understanding the visual context of the surrounding environment. Modern driver assistance systems and other automotive applications employ cameras to perform high-resolution tasks including environmental awareness, object classification, and color perception. Cameras are an essential part of Advanced Driver Assistance Systems (ADAS) and autonomous driving since they are utilized to recognize lane markings, traffic lights, and other vehicles. They furthermore offer visual data about the environment.

In order for cameras to function, light from the outside must shine on a collection of photosensitive cells. This produces a photoelectric effect, which produces an electrical charge. The corresponding row pixel unit is chosen by the row selection unit, and the image signals within it are sent via the signal bus of each column to the corresponding analogue

signal processing unit and digital-to-analog conversion circuit, where they are transformed into digital image signals and output [17].

The cameras may use daylight during the day, unlike LiDAR. In full light, it can identify things at a distance with a greater resolution and at a cheaper cost. It can even distinguish the color of automobiles and traffic lights. It does, however, also have certain drawbacks. For instance, it is easily impacted by weather conditions such as rain or snow, changes in light greatly affect its recognition accuracy, and current camera technology has trouble identifying far-off objects in still photos.

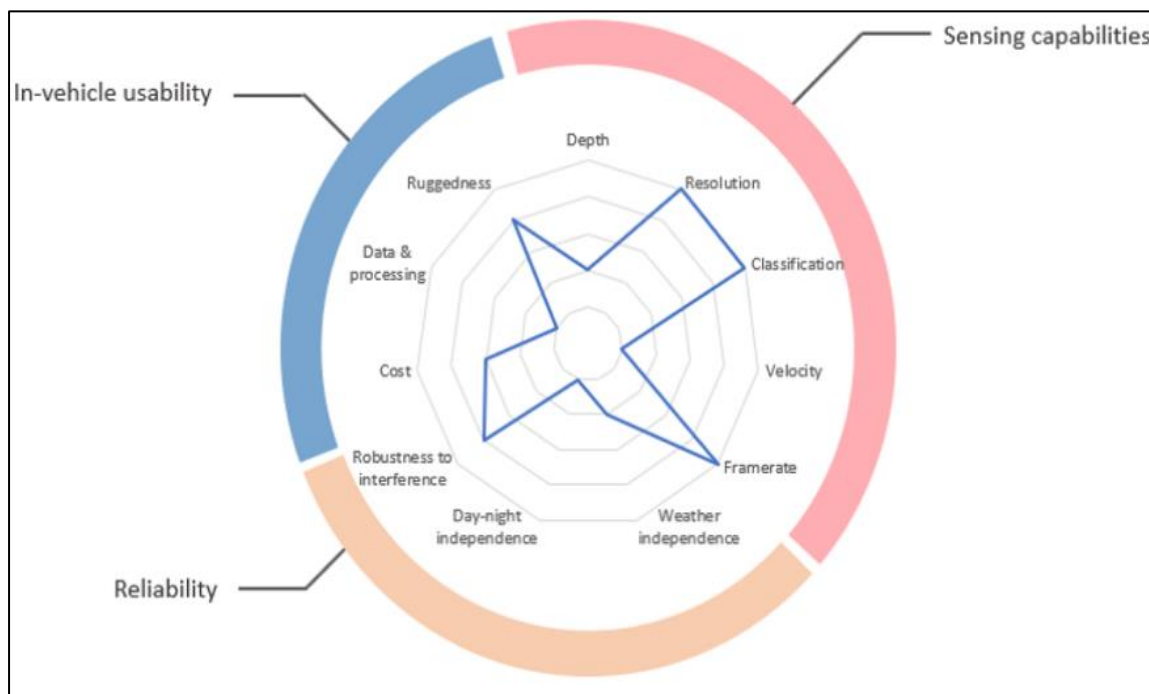


Figure 4. Camera attribute ratings for autonomous applications [18]

3.2 LiDAR

Real-time environmental data sensing and the creation of high-definition 3D visuals are both possible with LiDAR technology. In order to determine distance, LiDAR uses pulse modulated light to produce light, measure several light beams simultaneously or scan multiple beams of light at the same time to gather angle information[19]. Among the known environmental measurement options, it is the sensor solution with the best measurement accuracy due to its benefits of rapid response, extended detection distance, and high precision.

Noise will always be present in the point cloud data that the on-board LiDAR system collects because of things like acceleration, deceleration, changing driving directions, and other things.[12]

The majority of on-board LiDAR systems can now offer the intensity information of the reflected pulse, which is a reflection of various objects' attributes and the energy reflected from the target surface. However, the intensity information reflected by the laser point cloud will also change significantly depending on the LiDAR systems, the weather, or other particular factors. Furthermore, the LiDAR point cloud data obtained on-board is a form of blind data.

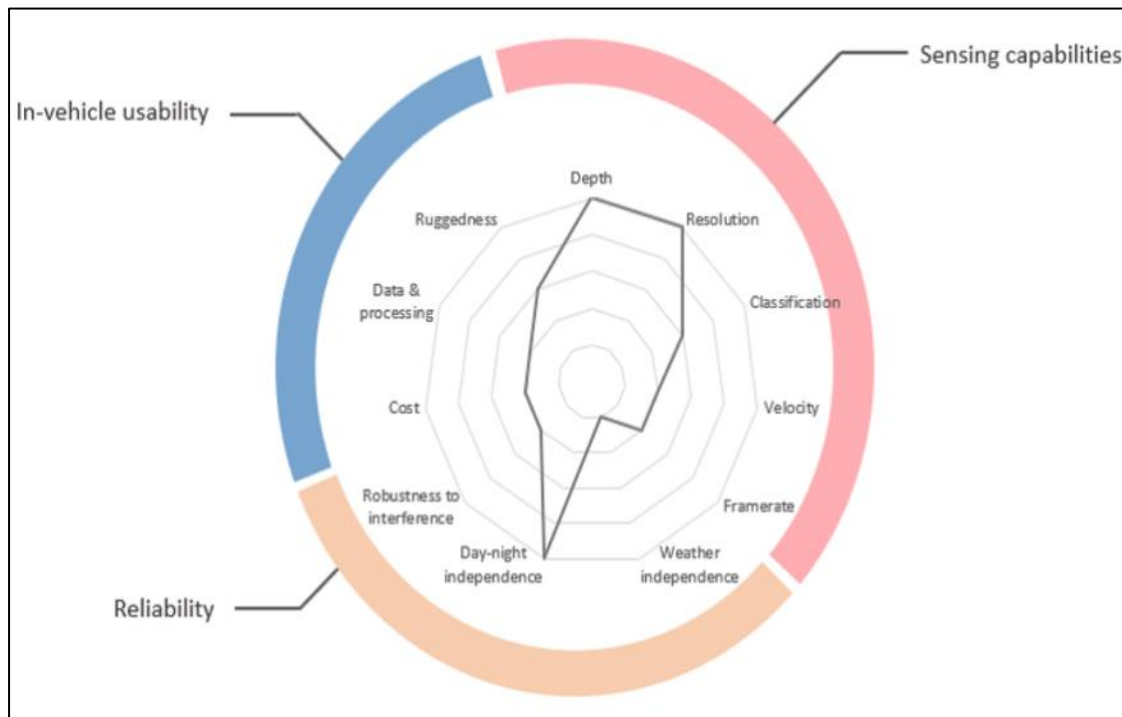


Figure 5. LiDAR attribute ratings for autonomous applications [18]

3.3 Radar

Radar (Radio Detection and Ranging) sensors make use of radio waves to measure an object's size, location, and speed. They are helpful for discovering things, especially in inclement weather conditions like fog or rain. Radar is used for collision avoidance, adaptive cruise control, and blind-spot monitoring. A sensor called radar utilizes radio waves to identify objects in its surroundings.

Radar has been used for decades to measure the location, velocity, and direction of moving objects. It was first developed before World War II. It works by aiming electromagnetic (EM) radio waves in a certain direction and watching for the reflections of any "illuminated" objects. Radar sensors are generally weather resistant and functional in all illumination conditions, including heavy rain, fog, blizzards, etc. Radars typically operate at 24 GHz, 77 GHz, and 79 GHz [20]

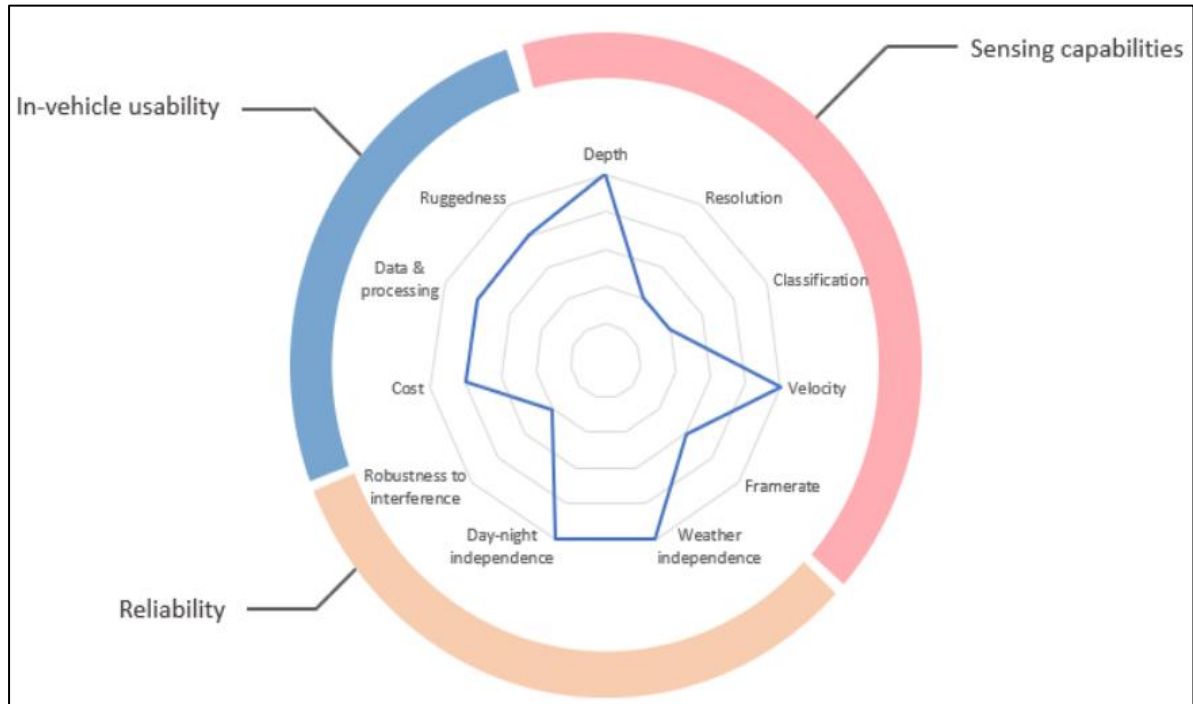


Figure 6. RADAR attribute ratings for autonomous applications [18].

4 Risk Assessment

Risk assessment is one of the most crucial components in creating safe and efficient autonomous vehicles. Autonomous vehicles need to be able to anticipate when a collision is likely to occur and adjust their maneuvering strategy accordingly [21]. Using trajectory data to determine the risk that drivers face based on how repellent they find a car to follow is one method that has been proposed [22]. Another approach involves analyzing severity indications in the vicinity of the self-driving car on a multifactorial basis, including time intervals, distance-based indicators, and traffic congestion indicators [23]. Furthermore, since using massive amounts of data from autonomous vehicles may result in more accurate risk

assessment and auto insurance pricing, actuarial modelling and risk management are growing increasingly interested in doing so. [24] For autonomous driving to be implemented, continuous risk assessments are necessary, despite the challenges posed by the unpredictable actions of human drivers in close proximity [25].

4.1 Criteria

The confusion and potential danger caused by the sensors' field of vision are a frequent corner case in the safety concern with autonomous driving. This is known as a "potential danger scene" and might lead to unanticipated conflicts when an autonomous vehicle (AV) is operating in the present driving area and another traffic participant (TP) enters the region from which the AV's optical sensor's view field is obstructed [26], [27]. When people unexpectedly enter the car's driving area and the AV is unable to respond in time, traffic accidents happen [28]. The safety, stability, and fundamental efficiency of autonomous cars are significantly impacted by the performance, reliability, compatibility, and maintainability of its sensors.

4.1.1 Performance

Sensor performance is critical for accurate data collection and decision-making in an AV's many systems, including as its propulsion, safety, and battery management systems. High-performance sensors can provide reliable data and precise measurements, which enhances the control and optimization of AV functions. Sensor performance is affected by a number of characteristics, including resolution, accuracy, response time, and the ability to function in a range of environmental conditions (such as vibrations, electromagnetic interference, and extreme temperature changes).

4.1.2 Reliability

A sensor's lifetime affects its long-term dependability and economics. A sensor's lifespan may vary significantly depending on its sort, quality, and usage conditions. LiDAR and radar are two examples of sensors with longer lifespans than others. The lifespan of the sensor is influenced by the quality of the materials, calibration, and maintenance practices.

4.1.3 Compatibility

Compatibility refers to how effectively sensors function with the hardware and software of the overall electric vehicle system. Sensors need to work with the AV's data interfaces, control systems, and communication protocols in order to guarantee smooth and reliable functioning. Compatibility must be guaranteed at an AV's design and integration stages in order to prevent issues with data integration and system reliability.

4.1.4 Maintainability

Maintainability is the ease with which sensors can be adjusted, calibrated, and replaced as needed. EV sensors need to be calibrated and maintained on a regular basis to ensure reliable and accurate data. The lifespan of sensors can also be extended by routine maintenance. Replacement parts, diagnostic tools, and service expertise must all be easily accessible in order to maintain and service sensors correctly.

In order to increase performance, reliability, and safety, electric car makers and researchers are continuously developing sensor technology. It is essential to follow manufacturer guidelines and undertake periodic maintenance to ensure that sensors function at their peak throughout the whole life of an AV. General and dynamic risk factor studies are needed to assess potential threats related to safety sensors like cameras, LiDAR, radar, and IMUs that are currently used in autonomous vehicles.

4.2 Generic Risk Assessment

The development of advanced safety sensors is critical to the ability of autonomous vehicles to traverse their ever-changing and complicated surroundings. Nevertheless, a number of risk variables may affect the reliability and effectiveness of these safety sensors, thereby affecting their performance. This article will examine common, broad risk variables that autonomous cars encounter with regard to safety sensors. These elements include environmental difficulties, sensor constraints, fusion problems, hardware and software vulnerabilities, cybersecurity issues, and legal and regulatory issues.

4.2.1 Environmental Factors

Due to the vast range of environmental circumstances in which they operate, autonomous automobiles are susceptible to things like inclement weather and low visibility. Unfavorable

meteorological circumstances, such as intense rain, snow, or fog, might impede sensor inputs, so impacting their precision. Sensor systems that depend on good visual input are challenged by poor sight, particularly at night or in low light.

4.2.2 Limitations of the Sensor

LiDAR, radar, and cameras are only a few of the sensors used by autonomous cars; each has limits of its own. These restrictions might include challenges with accuracy, poor resolution, and restricted range. For example, LiDAR sensors could have trouble precisely identifying things far away, and cameras might have trouble in dimly lit areas.

4.2.3 Problems with Sensor Fusion or Interference

For autonomous cars to produce a complete and accurate picture of their surroundings, sensor fusion is essential. Nevertheless, difficulties occur when combining data from several sensors, which causes disparities in how the world is seen. The overall dependability of the sensor suite may be jeopardized by sensor interference, which occurs when signals from one sensor interfere with the operation of another.

4.2.4 Vulnerabilities in Software and Hardware

Safety sensors might have weaknesses in both their hardware and software components. Software errors, malfunctions, or algorithmic deficiencies can result in inaccurate sensor readings and, as a result, poor decision-making on the part of the autonomous system. The whole integrity of the sensor suite may be jeopardized by hardware malfunctions, whether they are the result of wear and tear or manufacture flaws.

4.2.5 Cybersecurity and Data Privacy

Cyberattacks on safety sensors grow increasingly likely as autonomous cars get more networked. Malicious actors may be able to obtain unauthorized access to sensor data or manipulate sensor inputs by taking advantage of communication network weaknesses in the vehicle. Strong cybersecurity safeguards are essential for both the security of the car and the private information that the sensors are collecting.

4.2.6 Sensor Usage's Legal and Regulatory Status

The legal and regulatory environment surrounding self-driving cars is still developing, which raises questions regarding the obligations and liabilities related to safety sensors. The broad acceptance of autonomous cars may be hampered by unclear legislation pertaining to their deployment and operation. Legal frameworks must be clear in order to guarantee accountability in the event that safety sensors are involved in accidents or system malfunctions.

Though their successful incorporation into society depends on resolving and minimizing the numerous risk variables impacting the reliability and effectiveness of safety sensors, autonomous cars have immense potential to revolutionize transportation. Future developments in autonomous driving technology will be largely shaped by environmental obstacles, sensor constraints, fusion problems, software and hardware weaknesses, cybersecurity risks, and legal and regulatory considerations. To overcome these obstacles and open the door to a safer and more effective autonomous driving experience, industry players and regulatory agencies must continue their research, development, and cooperation.

4.3 Dynamic Risk Assessment

The ever-changing environment where autonomous cars drive presents a challenging job for safety sensor assessment as these vehicles develop. It is essential to take into account dynamic risk variables, which might change over time or in reaction to particular circumstances, in addition to static risk factors. This article explores the importance of assessing safety sensors in autonomous vehicles while accounting for dynamic risk variables, such as the quick changes in traffic patterns and road infrastructure, the emergence of new risks like cyberattacks, the evolution of regulations, technological advancements, sensor upgrades, and the inevitable wear and tear over time.

4.3.1 Rapid Changes in Road Infrastructure and Traffic Patterns

Road signal upgrades, traffic pattern modifications, and building projects are just a few of the many changes that may be made to the road infrastructure. Safety sensors that depend on predetermined maps and static data may face difficulties as a result of these dynamic changes.

For autonomous vehicles to navigate safely, they need to be able to quickly adjust to changes in their surroundings. The capacity of safety sensors to identify and react to dynamic changes in traffic patterns and road infrastructure should be evaluated.

4.3.2 Emerging Risks and Cyberattacks

Autonomous cars are vulnerable to new threats due to their digital nature, including cyberattacks. As technology advances, so do the strategies used by bad actors to take advantage of security holes in safety sensor systems. Cybersecurity measures must be taken into account while evaluating safety sensors in order to guard against illegal access, data manipulation, and other malicious activity that might jeopardize the security of the car and its occupants.

4.3.3 Evolving Regulatory Requirements

Lawmakers' efforts to stay up with technology developments have resulted in a constant evolution of the regulatory frameworks regulating autonomous cars. Regulations can change, and this can affect how safety sensors work and comply. The capacity of safety sensors to adjust to changing regulatory requirements should be included in a thorough examination to make sure autonomous cars follow the law.

4.3.4 Technological Breakthroughs and Sensor Upgrades

Technology for autonomous driving is constantly evolving, with new developments and discoveries occurring often. Since safety sensors are the foundation of autonomous systems, they need to stay up to date with these developments. When assessing safety sensors, one should take into account how easily they can be updated to improve performance and how well-suited they are to emerging technologies. Upgrading sensors on a regular basis is essential to keeping autonomous cars safe and competitive in a constantly changing technical environment.

4.3.5 Wear and Tear Over Time

Like conventional automobiles, autonomous cars also experience wear and tear over time. The overall safety of the car may be impacted by the loss in sensor function brought on by this wear and tear. Safety sensors should be regularly inspected and evaluated in order to determine how long they will last and how wear and tear will affect their precision and

dependability. Sensor degradation can be addressed with predictive maintenance techniques before it poses a serious risk to public safety.

An integrated strategy is necessary for evaluating safety sensors in autonomous vehicles, taking into account both static risk factors and dynamic variables that may change over time or in reaction to particular circumstances. The assessment of safety sensors is complicated by a number of factors, including wear and tear over time, developing dangers, shifting regulatory requirements, technology advancements, and rapid changes in road infrastructure.

5 Technical Methods for AV Safety and Risk Assessment

Technical substitutes for the previously mentioned criteria are covered in the section that follows. [29]

5.1 Machine-Learning-Based Method

Providing a safe state output in a range of intricate street scenarios is the primary goal of the safety assurance system [30], [31]. Several machine learning strategies, like the following, may be applied to get around such blind spots:

5.1.1 Partially observable Markov decision process (POMDP)

The POMDP model is a method of decision-making that carries out a number of connected duties and issues in order to optimize its ideal outcomes within a certain amount of time[32]. The primary benefit of utilizing the POMDP model is its consideration of the uncertainty component in readings through "Partial Observability," which refers to the agent's reliance on a probability distribution across a set of all possible states rather than direct state observation. The collection of observations, their corresponding transitions, and their probabilities are then used to update this distribution. It is described by the tuple that follows [33]:

$$(S, A, T, Z, O, R, \alpha) \quad (1)$$

The belief state, which represents the agent's learned imperfect value, is represented as a probability distribution across the states[33]. Until every action and observation has been considered, this procedure is continually repeated[32].

5.1.2 Model predictive control (MPC)

This process control technique meets a predefined set of constraints. An autonomous vehicle's MPC model is created to both satisfy the vehicle's dimensions and physical constraints and keep the vehicle on its intended course[34]. While preserving the stability of the AV, MPCs may be simply implemented at several levels of the process control system, which incorporates diverse input and output dynamics. MPCs are more noticeable and effective in the AV's steering control. These provide the control system boundaries more stability as compared to linear controllers. In addition, the MPC establishes a standard against which linear and other suboptimal controllers can be evaluated.

Owing to these benefits, MPC models are used in a wide range of automotive subsystems, including traction control, proactive suspensions, active steering, and proactive braking systems, all of which work in tandem to enhance handling and stability [35]. Using its optimization framework, the vehicle can also generate its own motion in a given time horizon in AVs using the MPC approach. This is done while taking into account different constraints like the speed limit, neighboring vehicle trajectories, and states, as well as the mechanical constraints unique to AVs, like maximum acceleration and availability of braking torque [36].

5.1.3 Use of neural networks (NNs)

When it comes to estimating the range, severity, and impact of accidents, this is most likely the most effective way. The quantity of data input into this system determines its efficiency. It also depends on how properly the data points are labelled and how "clean" the data that is sent in. Typically, this is accomplished by splitting the data into independently created camera and LIDAR databases. The primary method of labelling three-dimensional LIDAR data is by creating 3D box labels for objects like cars, bikes, people, and street signs. Every scenario

may have unlabeled sections, also referred to as the no label zone (NLZ), which are shown as polygons in collected frames[37].

Each LIDAR point is given a Boolean data type that indicates whether or not it is an NLZ in order to distinguish them from box labels. labelling a two-dimensional camera picture using 2D bounding boxes is how two-dimensional camera labelling is accomplished[38]. These labels have worldwide unique tracking IDs, are well specified, and fit a certain way. Typically, items with 2D labels include bicycles, people, and cars. The training and test datasets are then created from this tagged data. The model is trained using the training set, and its accuracy is evaluated using the test set[34].

It is mentioned that the test set ought to be big enough to produce statistically significant results, contain every feature of the entire dataset, and not exclude any feature from the test dataset; in other words, the test dataset ought to be a subset of the training dataset. It should be mentioned that the training data shouldn't be overfitted by the model. Until the desired degree of precision is reached, this process is repeated. This highly trained deep learning approach [39] is used by the autonomous vehicle's system to recognize objects and spatial characteristics utilizing CNNs and SCNNs. The on-board ADS and ADAS system then analyze these features to provide the appropriate output.

Since CNNs are unable to identify the "spatial features" of surrounding objects, SCNNs are more appropriate in this situation. When it comes to lane detection, the SCNN "extrapolates" the lane markings when the lanes are obscured by objects like cars, poles, road dividers, pavements, etc., while CNNs, which are unable to detect spatial features, display a discontinuity when detecting lanes obscured by objects[40].

By creating slice-by-slice convolutions from typical deep layer-by-layer detected convolutions, SCNNs enable message transfer across pixels throughout the layer's rows and columns. Large objects having strong "spatial" relationships, such as traffic poles, lanes, curving lanes, pillars, walls (road dividers), etc., may be detected by SCNNs with significant accuracy[40].

5.2 Cooperative Collision Avoidance Based Method

A cooperative collision avoidance system (CCA) can also be used to tackle the safety issue when the vehicle operates outside of its ODD [41]. The use of CCA systems holds great potential in mitigating traffic congestion and accident rates[42]. There have been several documented attempts to prevent collisions using the V2V communication approach in situations such frontal collisions brought on either abrupt or abrupt braking. Because of its great sensitivity to time, the CCA system needs extremely impromptu decision-making algorithms and actuators to enable the necessary maneuvers[43]. In order to better address and comprehend this problem, this research investigates the decision-making algorithms supported by V2V communication by going over and simulating high-risk scenarios. The majority of emergency scenarios (hazardous ODD) and emergency circumstances may be primarily visualized using a CCA maneuvering scenario[41]. The car entering from the neighboring lane during a collision avoidance technique is often referred to as an ego vehicle. One of the most important decisions the vehicle makes is whether to accelerate or decelerate and whether to engage or disengage the elastic band maneuver. The examples illustrate that the car needs vehicle-to-vehicle (V2V) communication in order to detect the real-time location of other vehicles and avoid them. A vehicle is seen to remain on a predefined course in the absence of V2V or V2X communication [44].

5.2.1 Path following

The primary tasks of the path following system are to compute the error margin and provide a virtual path map [41]. The path or virtual map is constructed using recorded GPS waypoints, previously recorded human driving, or data from a web map. Subsequently, the routes are separated into distinct segments, which are smaller sections of the road, with an equal quantity of data points in each segment. Here, a third-degree polynomial equation is used in [29]

$$x_i(\lambda) = a_{x_i} + b_{x_i}\lambda^2 + c_{x_i}\lambda + d_{x_i} \quad (2)$$

$$y_i(\lambda) = a_{y_i} + b_{y_i}\lambda^2 + c_{y_i}\lambda + d_{y_i} \quad (3)$$

All of the route or virtual maps that make up the equation's a, b, c, and d coefficients are developed offline. Next, these created coefficients are employed for the error computation. The vehicle position, chosen preview distance, and the curvature of the vehicle route may all be used to assess and quantify the mistakes in yaw angle and lateral deviation [29].

5.2.2 Collision avoidance with elastic band system

This method replaces the path-following system. The collision avoidance mode is triggered when an item or another vehicle arrives on or close to the ego vehicle's route. Forces pointing in the obstacle's direction change the path points close to the vehicle. Data points are created online as the vehicle proceeds along the course, although with a changed path [45].

The collision avoidance system is mostly restricted to emergency or abrupt lane changes, with the elastic band technique being used more frequently for path following tasks where there is already a specified path that runs between the lanes[41]. The path is divided into nodes that are successively linked by these "elastic strings" to depict this predetermined course. An internal force $\mathbf{F}_{int}$ holds the curved path together.

When the ego vehicle deviates from the planned course, $\mathbf{F}_{ei}$, an outside force, takes action. These forces cause the ego vehicle's route to "bend" like an elastic band; the ego vehicle's path's curvature is determined by the strength of these forces. In this case, the internal force at work, $\mathbf{F}_{int}$, and outside force $\mathbf{F}_{ei}$ may be expressed mathematically as[29]

$$F_{int}^{*i} - F_{int}^i = K_s(u_{i+1} - u_i) \quad (4)$$

$$F_{ei} = -[K_s(u_{i+1} - u_i) + K_s(u_{i-1} - u_i)] \quad (5)$$

Thus, by repeating the iteration for every node, the overall route of the ego vehicle can be constructed. These equations may also be used to determine the needed displacement for each node owing to $\mathbf{F}_{int}$ and $\mathbf{F}_{ei}$.

5.2.3 Decision making and lane shifting

In order to avoid a collision, the autonomous vehicle (AV) must take into account both approaching cars and objects in the next lane in addition to any other vehicles in the same

lane or in its current route. The ego car may be arriving from the same way or the other direction depending on the oncoming vehicle in the next lane[46]. The algorithm is implemented by the system. [29]

$$x_2 = x_1 + (v_a - v_e)t_m + x_s \quad (6)$$

Where,

X_2 = New position

X_1 = old position

V_a =velocity of adjacent vehicle

V_e =velocity of ego vehicle

T_m =maneuver time

X_s = safety distance

Nonetheless, the equation indicates that there is still a chance of a collision for the cars in the neighboring lanes. The direction of movement does not need to be changed if, after this computation is repeated step-by-step, the ego vehicle is in the danger zone in the longitudinal direction. It slows down ideally until the danger zone passes [47] rather than changing lanes.

6 Algorithm development

To mitigate the hindrance to efficient sensor system, an efficient decision-making algorithm should be generated. Based on current research, sensor fusion will be used to collect the sensor data from various sources of sensors and RadChat [49] will be used to remove the R2R interference. But to get the best of their ability, autonomous cars need to be fast in sensing like a human driver perception. Reducing response time and reducing the redundant data overlapping, the goal can be achieved.

Analyzing the contributing causes and issues reveals that self-driving cars lack the rapid reaction time of a human driver. Without an effective system, there will be more data

collected after multi-sensor fusion than is necessary. The system may become less effective as a result, and environmental problems may increase.

The main step will be to increase algorithmic efficiency in order to minimize the hardware limitations and bypassing them. It will let the vehicle utilize its resources and capability in a full context.

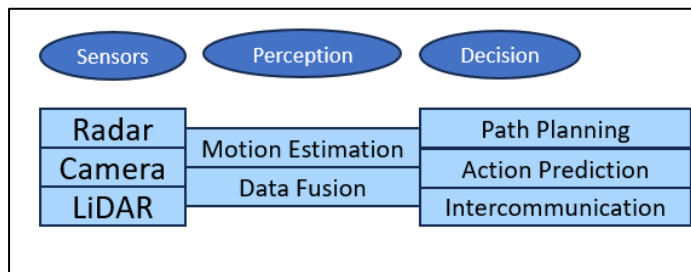


Figure 7 Primary analysis to set the bias.

6.1 Hypothesis of efficiency algorithms

Several approaches for merging Camera, LiDAR, and Radar sensor data have been proposed in studies to improve AV perception. Unfortunately, past techniques are not robust enough in difficult driving conditions because of the stiffness in their fusion implementations. These methods may be roughly classified into two groups: (i) late fusion, which produces worse estimates since it cannot utilize features from several sensors, and (ii) early fusion, which works badly when sensor data is noisy or obstructed. HydraFusion, a selective sensor fusion design that maximizes robustness without losing efficiency, can be utilized to get around these problems. [50]

Our solution, called "Priority Biased Fusion," involves adding bias to Hydra fusion in order to improve accuracy while reducing reaction time with the least amount of computing effort. This will address the When and Where queries similar to a human driver's propensity for making decisions. By introducing bias and prioritizing incoming information, our approach will improve the automated vehicle decision-making system's responsiveness. Stimuli should be prioritized in decision-making by assessing the effectiveness and responsiveness of different technologies as well as their impact on the overall functioning.

To get the most precise estimate possible, several measurements must be combined. From a general perspective, we try to model the link between the measurement we want to estimate and the parameter. This may be accomplished using the following standard parameter estimate formulation [51]:

$$x = H_y + e \quad (11.)$$

After that, the squared error should be minimized with respect to y .

$$\min_y \|x - H_e\|^2 \quad (12.)$$

Next, we will take the partial derivative with respect to y and set it to 0. The solution may then be transformed into a weighted least-squares by the noise covariance matrix as follows, assuming the error, e , and the model $E(e) = 0$ with $E(ee') = R$ where R is the error covariance:

$$\hat{y} = (H^T R^{-1} H)^{-1} \cdot H^T R^{-1} x \quad (13.)$$

Taking into account the scenario of combining n sensor readings. The unbiased minimal variance estimator is expressed as follows:

$$\hat{y}(n) = \left[\sum_{i=1}^n H_i^T R_i^{-1} H_i \right]^{-1} \cdot \sum_{i=1}^n H_i^T R_i^{-1} x_i \quad (14.)$$

Where,

y = The true estimated parameter of dimension n_y

x = The measurements to be fused of dimension n_x

H = An $n_x \times n_y$ measurement matrix that provides a mapping between the state of the system to the measurements

e = The estimation error

R = The error covariance

Performance of a fusion filter is mostly improved with increased information. Nevertheless, this logic fails when additional causes of estimating mistakes are present, such as differences in the measurement models. These situations can have a detrimental effect on the accuracy of sensor readings and are frequently encountered in autonomous driving [52].

After this, we will set the parameter for creating a bias. Assume, the parameter matrix to be P . Now, we will create the priorities separately for camera, lidar and radar as α_c , α_L and α_R . If we set the coefficients, we can get the general priority equation,

$$P_{n_x, n_y} = C \cdot \alpha_c + L \cdot \alpha_L + R \cdot \alpha_R \quad (15.)$$

Then, we will add this to the module of variance estimator.

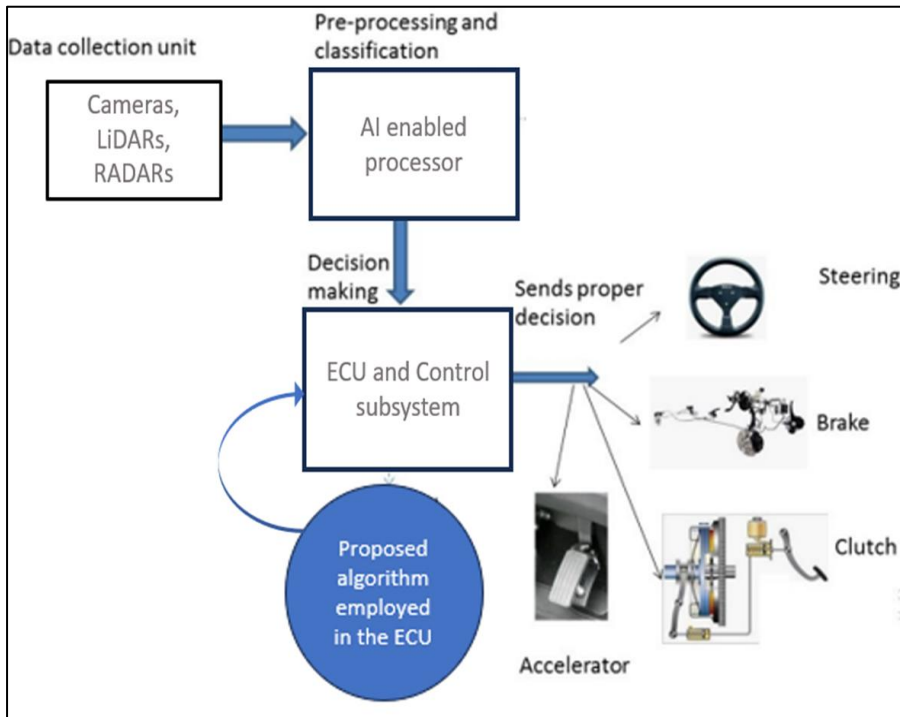


Figure 8, Working diagram of proposed efficiency algorithm (self-illustrated from [53])

6.2 Workflow of generating and validating efficiency algorithm

There are specific procedures that may be followed to obtain an efficient algorithm, which will result in a fully verified algorithm that reduces reaction time and superfluous sensor data for multi-sensor fusion.

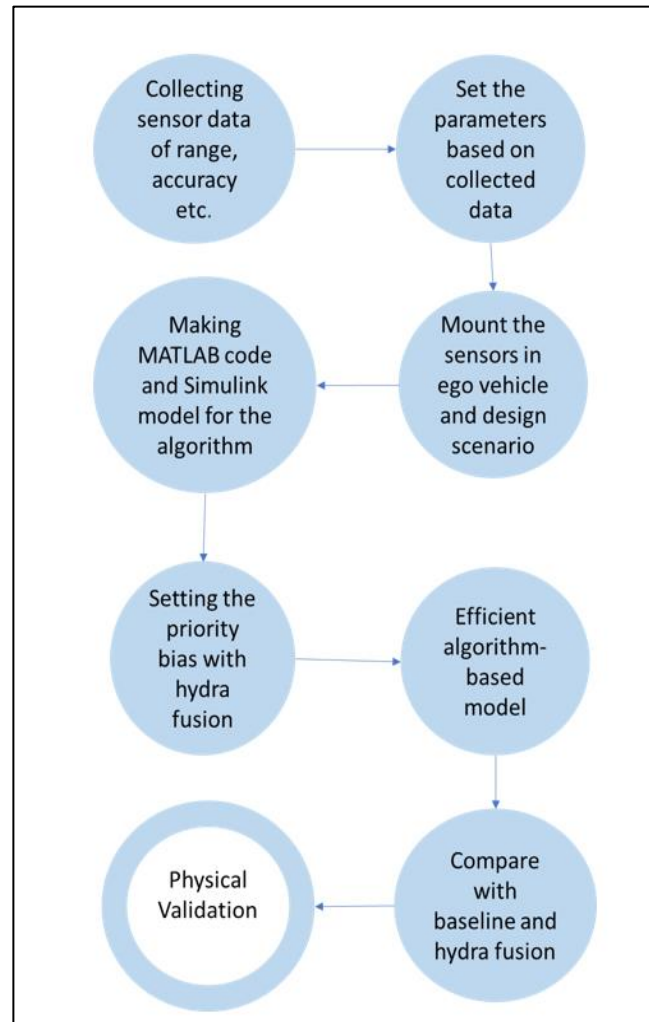


Figure 9, Workflow of generation of efficiency algorithm.

From the workflow, data collection, parameter and MATLAB code is added in the annex,

6.3 Results

After data collection and code, the entire Simulink model had been made with small subsystems. The platform Driving Scenario Designer has been used for the base model.

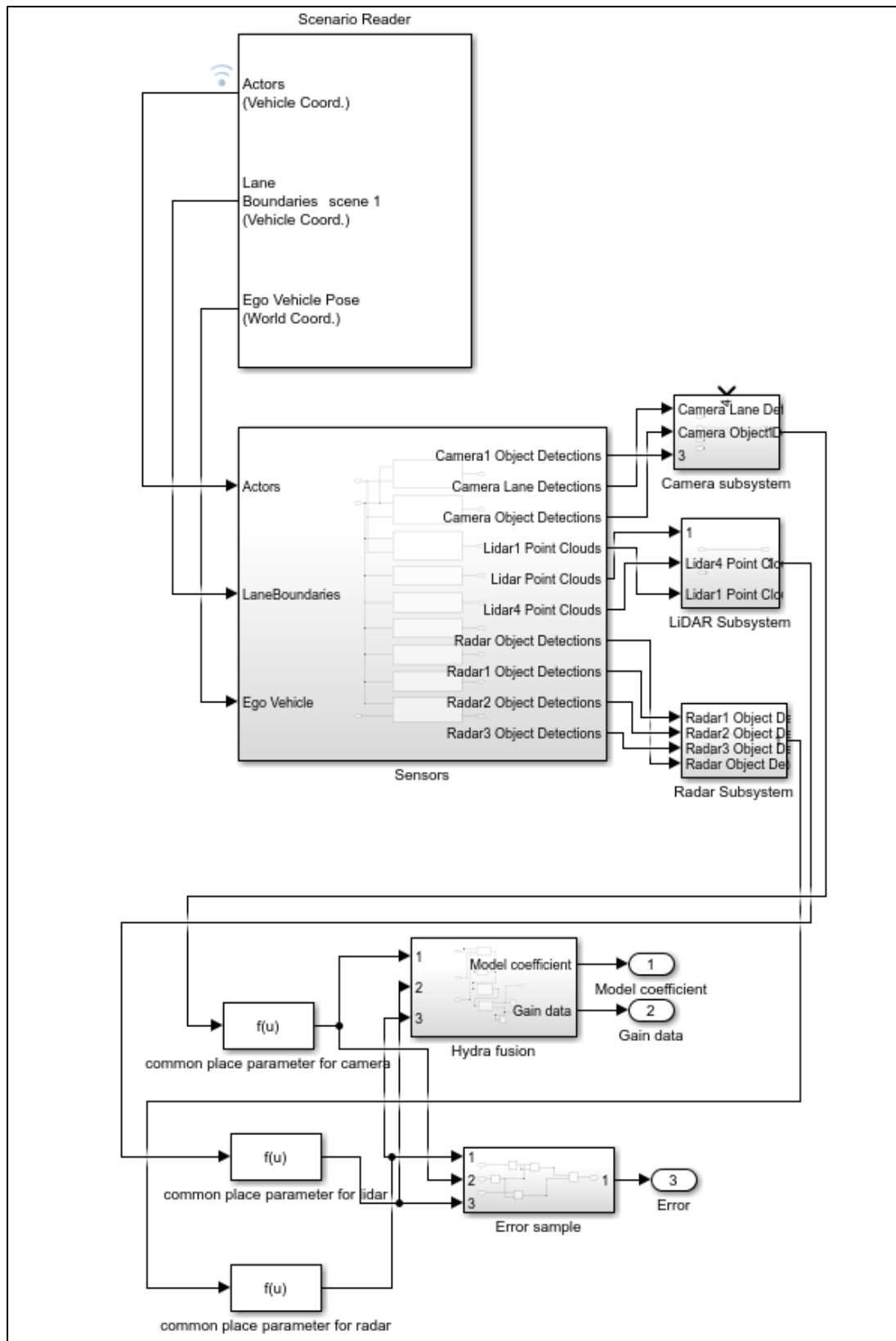


Figure 10, Simulink model for the entire system.

Finally, the coordinate and the reference were added to this track. We have designed this track following the curves, banking, crossing and relevant possible complexities.

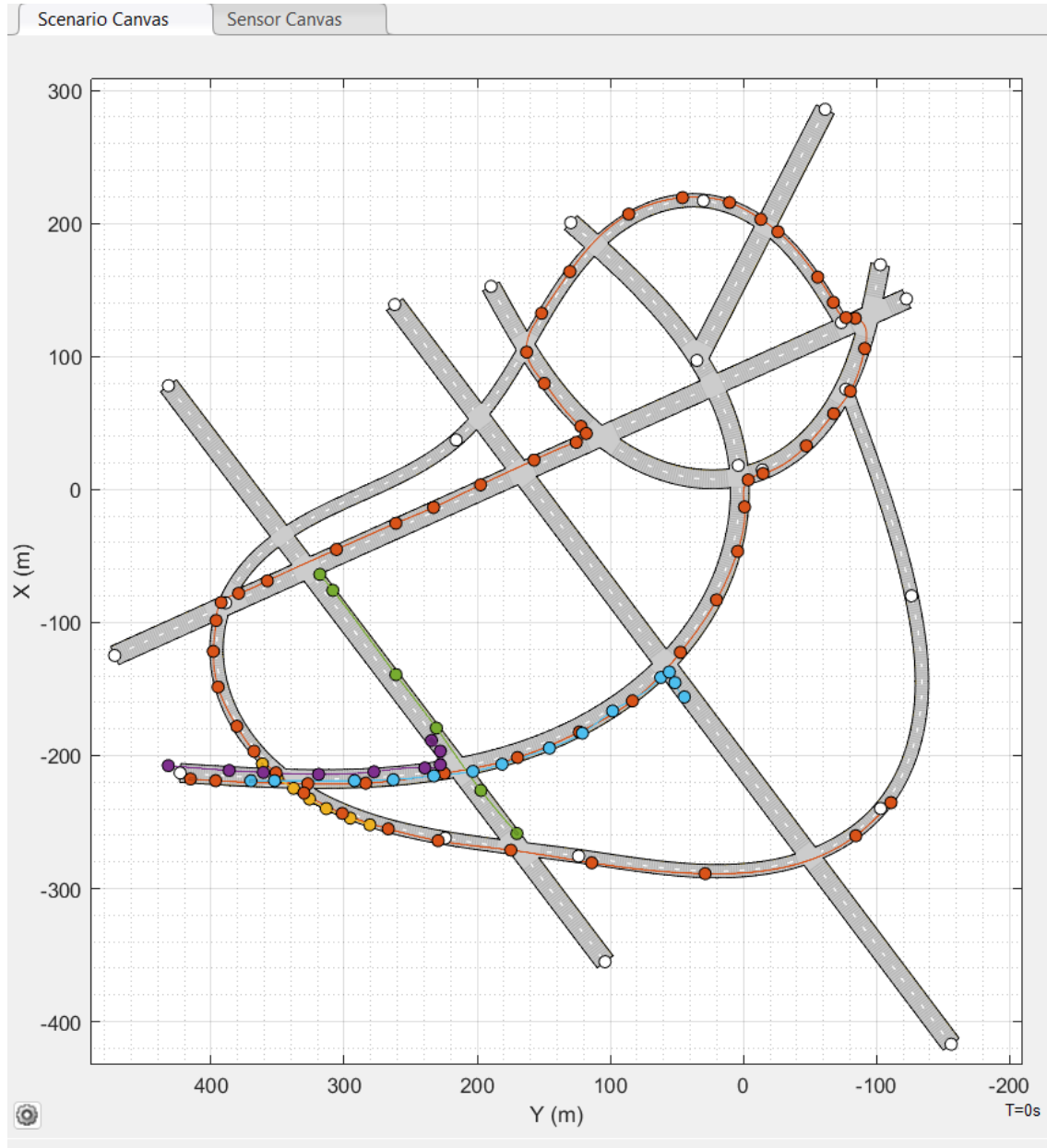


Figure 11, Designed track to validate.

For the result, we have simulated the entire path with different velocities and jerks. The sample is taken from time 0s to 10s. It can be seen that the ego vehicle is using only LiDAR sensor here for the rare vehicle. It is using Camera for lane detection. When there

is any crossing or any close passing car or bicycle from the same direction appears, the radar is activated as the first priority.

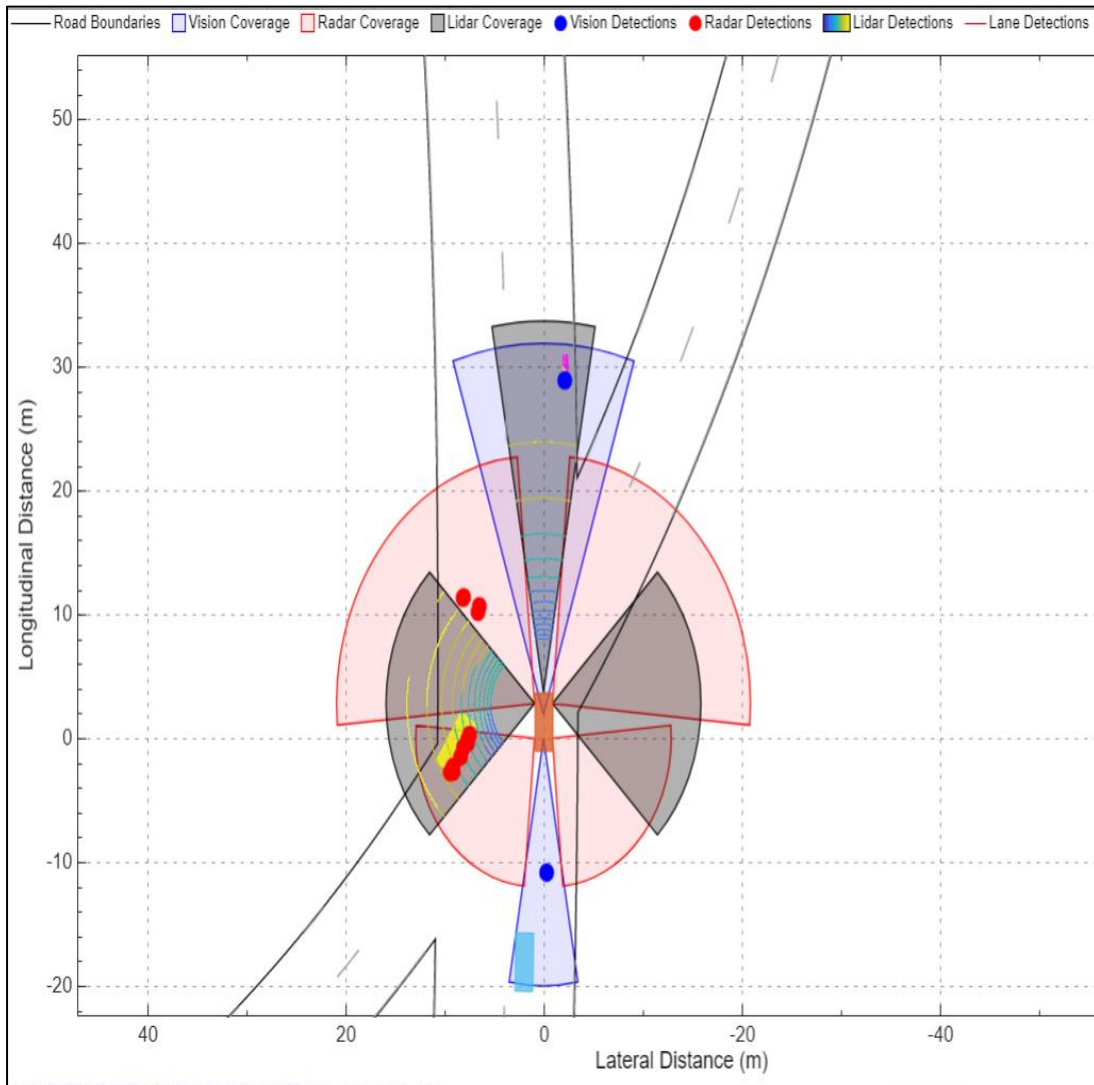


Figure 12. Bird Eye View of a sample simulation to detect priority.

After the simulation, we have made the comparison between the baseline model, Hydra Fusion model and our Efficient Decision-Making Priority Biased model.

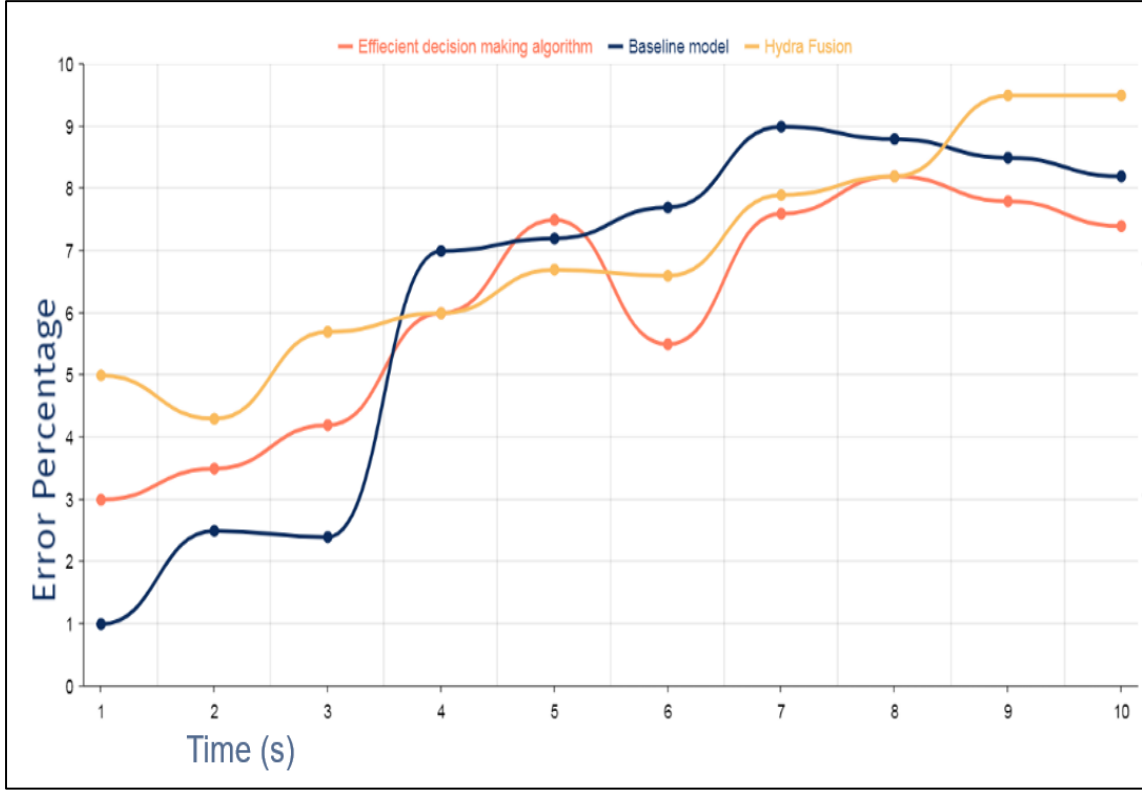


Figure 13. Comparison between the baseline, Hydra and proposed algorithm-based model.

From the graph above initially proposed algorithm has more error than baseline model which comes to stable stage after 7s. After crossing obstacle on 5s, it performs better than baseline model.

7 Comparison of sensing capabilities of human drivers and sensors in AV

Autonomous vehicles (AVs) are causing a revolutionary shift in the automobile sector as technology advances. The comparison of human drivers' detecting abilities with the advanced sensor systems built into autonomous cars is a crucial part of this shift. The present examination delves into the subtleties of perception, situational awareness, and flexibility, elucidating the advantages and disadvantages of both autonomous vehicles and human drivers.

To navigate the complexity of the road, human drivers use a variety of sensory inputs, including vision, hearing, touch, and cognitive processing. As a dominating sense, vision enables drivers to decipher a wide range of visual cues, including traffic lights, road signs,

and other cars' movements. Real-time processing of this visual data by the human brain facilitates prompt decision-making and flexible reactions to changing circumstances.

Human drivers use audible signals in addition to eyesight to identify sirens, honks, and other pertinent noises that enhance their situational awareness. Touch contributes to pedal and steering control by offering a tactile link to the dynamics of the vehicle. In addition, human drivers are naturally perceptive to nonverbal signs and social cues, which helps them communicate with pedestrians and other drivers.

In contrast, autonomous cars use a variety of sensors, including LiDAR, radar, cameras, and ultrasonic sensors, to sense and understand their environment. LiDAR systems use laser beams to measure distances precisely and produce intricate 3D maps of their surroundings. Radar sensors are especially useful in inclement weather since they employ radio waves to identify objects and their velocities. Visual information is provided by cameras, while close-range object recognition is aided by ultrasonic sensors.

By combining various senses, AVs are able to obtain a thorough, all-encompassing perspective of their environment. The car can recognize and react to a variety of events, from negotiating complicated traffic to spotting pedestrians and bicycles, thanks to machine learning algorithms that interpret the sensor data. In contrast to human drivers, autonomous vehicles (AVs) do not experience weariness, allowing them to remain vigilant throughout the duration of the journey.

In general, machines and computers are ideally adapted for jobs like driving, particularly when it comes to consistency, multichannel information processing, power output and control, and reaction time (speed). While driving, human drivers still often have an edge in terms of observation, logic, and sensing. Autonomous vehicles (AVs) must use a range of sensors to match or surpass human sensing skills. This necessitates total sensor fusion throughout the system, which combines all sensor inputs to provide a single, cohesive image of the surrounding environment and highway. While no one sensor can fully replace a human's senses, several do provide skills that a human driver could not match. With a greater working range and omnidirectional communication that does not require an unobstructed line of sight, as human drivers and AVs often do, the integration of connected-vehicle technology expands the effective range and coverage area of both human-driven cars and AVs. The

potential awareness of other road users and road conditions is maximized when human-driven cars, or autonomous vehicles (AVs), that can "see" traffic and their surroundings, are combined with connected vehicles (CVs), which can "talk" to other traffic and its surroundings. For the purpose of detecting any road user or obstruction that is not a part of the integrated dedicated short-range communications (DSRC) system that CVs employ, AV sensing will still be essential. When operating cars at NHTSA automation levels 4 and 5, a fully functional linked autonomous vehicle presents the best chance to replace the human driver in an efficient and safe manner [48].

While human drivers are superior at making intuitive decisions, exhibiting emotional intelligence, and deciphering intricate social circumstances, autonomous vehicles (AV) sensors provide unmatched accuracy, dependability, and round-the-clock watchfulness. While AV sensors function with steady focus, unaffected by human limits like weariness and emotional states, human drivers may be more prone to distractions and other factors that might impair their performance.

Nonetheless, artificial intelligence (AV) still faces difficulties in matching human inventiveness, flexibility, and sophisticated comprehension of uncertain circumstances. Human drivers are adept at interpreting nonverbal clues, navigating confusing situations, and quickly adapting to changing circumstances. Even with their great advancements, AV sensors might have trouble in circumstances when people behave erratically or in unusual ways on the road.

Performance aspect	Human	AV			CV	CAV
		<i>Radar</i>	<i>Lidar</i>	<i>Camera</i>	<i>DSRC</i>	<i>CV+AV</i>
Object detection	Good	Good	Good	Fair	n/a	Good
Object classification	Good	Poor	Fair	Good	n/a	Good
Distance estimation	Fair	Good	Good	Fair	Good	Good
Edge detection	Good	Poor	Good	Good	n/a	Good
Lane tracking	Good	Poor	Poor	Good	n/a	Good
Visibility range	Good	Good	Fair	Fair	Good	Good
Poor weather performance	Fair	Good	Fair	Poor	Good	Good
Dark or low illumination performance	Poor	Good	Good	Fair	n/a	Good
Ability to communicate with other traffic and infrastructure	Poor	n/a	n/a	n/a	Good	Good

Figure 14. Sensing capability comparison [12]

The comparison of autonomous vehicle sensors and human drivers' senses in the dynamic field of transportation reveals a complex interaction between accuracy, flexibility, and intuition. When it comes to cognitive and emotional intelligence, human drivers are superior to automated vehicles (AV) because of their consistency, accuracy, and 360-degree awareness. The smooth integration of autonomous cars into our transportation networks will depend on finding a balance between technical advancements and human factors.

8 Conclusion

In this research, a sensor fusion framework that can selectively fuse sensor inputs in a context-aware manner is being focused and validated. It was validated through theoretical, qualitative, and quantitative analysis on the task of object detection performed on a challenging real-world dataset. It can be improved with more features to have comparable less energy consumption, latency, and memory usage to existing fusion architectures.

The significance of evaluating both general and dynamic risks has been highlighted by the investigation of risk assessment methodologies.

Examining how autonomous car sensors make decisions like human drivers is a noteworthy feature of this study. Autonomous car sensors excel in accuracy, consistency, and real-time processing of large volumes of data, but human drivers are more intuitive decision makers, flexible in unexpected situations, and emotionally intelligent. Achieving a seamless integration of autonomous car sensors into our transportation scene requires finding a balance between the cognitive abilities of human drivers and their technical capabilities.

This sensor may have some limitations as it has been evaluated with a small dataset and specific driving scenarios. The probability of false negative and false negative responses can be checked for future work. This model has no specifications of working in adverse weather and anomaly conditions yet. Addition to this, minimizing redundancy and errors will be the main goal to proceed to perfect result with better outlook. Using Large Language Model (LLM) based model can be helpful in this context.

Essentially, the study has offered a comprehensive investigation of autonomous vehicle sensors, acknowledging the complex interactions among risk variables, software,

hardware, and decision-making processes. Research, development, and cooperation will be crucial as autonomous driving advances in order to tackle the problems that have been found and move the technology towards a time when efficiency, safety, and human-machine cooperation are all seamlessly integrated into autonomous cars.

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10 Annex

10.1 Data collection

To establish a bias, it is necessary to collect the requisite camera, lidar, and radar data. To further set the priority bias, data on range and response time for widely used cameras must be collected. Knowing the response time and how the cameras are behaving within a certain range might help to set priorities.

Table 1. Current camera and their range with response time

Camera model	Range (meter)	Response time(min)
RC Visard 160	0.5-3	0.5
Framos D435e	0.2-10	0.2
Intel D455	20	0.4
Intel D415	10	0.16
Intel D435	10	0.105

Collecting range and the response time data for current LiDAR is necessary to prioritize the response required for driving conditions to detect.

Table 2. Current LiDAR and their range with accuracy

LIDAR model	Range(meter)	Accuracy %
Velodyne VLP-16	100	+/- 0.03
Velodyne VLP-32C	200	+/- 0.03
Velodyne VLS 128 Alpha prime	245	+/- 0.03
Hesar Pandar 64	200	+/- 0.02
Leisher c16 700B	150	+/- 0.02
Robosense RS lidar 32	200	+/- 0.03

Collecting accuracy and precision data for current radars to set the priority bias later on. Undetected, detected percentage has been evaluated from below.

Table 3 Radar Measurements for RSC based model with accuracy[111].

		RCS-based Model		
		Undetected	Detected	Total
Radar Measurements	Undetected	6152	38011	44163
	Detected	5368	39048	44416
	Total	11520	77059	88579
→Accuracy = 51.03%. Precision = 50.67%, Recall = 87.91%				

10.2 Implementation

Firstly, we set the sensors with detection range and detection probability.

The positions of the sensors to be mount in the ego vehicle with their properties will be discussed below. This data will be used to define the co-efficient of priority algorithm.

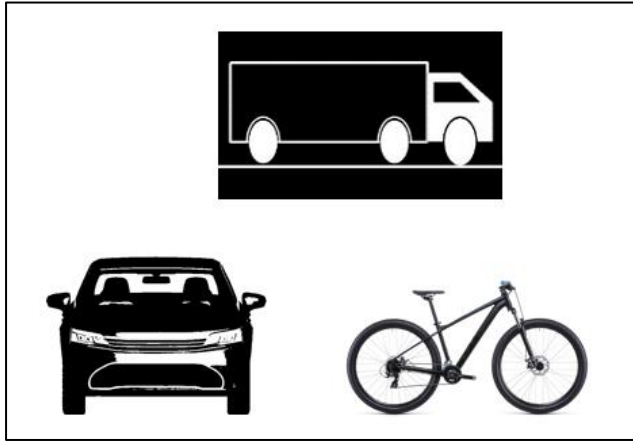
The sensors are mounted in a way that can cover 360° around the vehicle.

Table 4. Sensors with parameters to implement.

Sensor type	Placement	Detection range(m)	Detection Probability	Azimuth	Elevation
Camera 1	Middle back	20	0.7	-	-
Camera 2	Middle Front	30	0.9	-	-
LiDAR 1	Middle Front	30	0.02	0.16	1.25
LiDAR 2	Middle Left	15	0.05	0.16	1.25
LiDAR 3	Middle Right	15	0.05	0.16	1.25
RADAR 1	Left Front	24	0.9	90°	5°
RADAR 2	Right Front	24	0.9	90°	5°
RADAR 3	Left Back	12	0.7	90°	5°

RADAR 4	Right back	12	0.7	90°	5°
---------	------------	----	-----	-----	----

We have used the reference object as truck, 4-wheeler car and bicycle. It is prebuilt in MATLAB Driving Scenario Designer.



15.Fig. Reference object for implementation

After that, the pseudo code was made to process the sensor data. Here is the code for the basic sensor data processing.

Table 5. MATLAB Code for sensor data processing

```
function processSensorData(cameraData, lidarData, radarData)
    thresholdDistance = 10;
    crossingThreshold = 5;

    if isempty(lidarData) && isempty(radarData)
        disp('No sensor data available. ');
        return;
    end

    if ~isempty(lidarData) && any(lidarData > thresholdDistance)
        disp('Using lidar for objects more than 10m away. ');
        processLidarData(lidarData);
    end

    if ~isempty(cameraData)
        disp('Using camera for lane detection. ');
        processCameraData(cameraData);
    end

    if ~isempty(radarData) && any(radarData < thresholdDistance)
```

```

        disp('Using radar for objects less than 10m away and for
crossings.');
```

```

        processRadarData(radarData, crossingThreshold);
    end
end

function processLidarData(lidarData)
    disp('Processing lidar data.');
```

```

    % lidar processing code
end

function processCameraData(cameraData)

    disp('Processing camera data for lane detection.');
```

```

    % camera processing code for lane detection
end

function processRadarData(radarData, crossingThreshold)
    disp('Processing radar data for objects less than 10m away and for
crossings.');
```

```

    closeObjects = radarData(radarData < 10);
    if ~isempty(closeObjects)
        disp('Processing close objects detected by radar.');
```

```

    end

    crossingObjects = radarData(radarData < crossingThreshold);
    if ~isempty(crossingObjects)
        disp('Processing radar data for crossings.');
```

```

        % radar processing code for crossings
    end
end
end
```

For lane detection, we will be using this MATLAB base code.

Table 6. MATLAB Code for lane detection

```

function laneDetection(cameraImage)

    grayImage = rgb2gray(cameraImage);

    smoothedImage = imgaussfilt(grayImage, 3);

    edges = edge(smoothedImage, 'Canny');
```

```

    [H, T, ~] = hough(edges);
    peaks = houghpeaks(H, 10);
    lines = houghlines(edges, T, peaks);

    figure;
    imshow(cameraImage);
```

```

hold on;
    for k = 1:length(lines)
        xy = [lines(k).point1; lines(k).point2];
        plot(xy(:,1), xy(:,2), 'LineWidth', 2, 'Color', 'r');
    end

    hold off;
    title('Lane Detection');
end

```

For LiDAR data for collision avoidance, this has been followed.

Table 7. MATLAB Code for collision avoidance

```

function lidarCollisionAvoidance(lidarData)
    safeDistance = 5;
    if isempty(lidarData)
        disp('No lidar data available. ');
        return;
    end

    obstacles = lidarData(lidarData < safeDistance);
    if ~isempty(obstacles)
        disp('Collision detected! Taking evasive action. ');
        % collision avoidance algorithm
        stopVehicle();
    else
        disp('No collision detected. Proceeding safely. ');
        % normal driving algorithm
    end
end

function stopVehicle()
    disp('Stopping the vehicle! ');
    % code to stop or take action
end

```

For the noise variance and the proposed algorithm will be applied after that.

Table 8. MATLAB Code for Priority Bias Algorithm and Variance

```

H = cell(1, 99);
R = cell(1, 99);
x = cell(1, 99);
n = 99;

sum_HtRiH = zeros(size(H{1}));
sum_HtRiX = zeros(size(x{1}));

for i = 1:n

```

```

    term_HtRiH = H{i}' * inv(R{i}) * H{i};
    term_HtRiX = H{i}' * inv(R{i}) * x{i};

    sum_HtRiH = sum_HtRiH + term_HtRiH;
    sum_HtRiX = sum_HtRiX + term_HtRiX;
end

y_hat = inv(sum_HtRiH) * sum_HtRiX;

disp('Result of y_hat:');
disp(y_hat);

x1 = 10;
ve = 5;
va = 2;
tm = 3;
xs = 2;

x2 = x1 + (va - ve) * tm + xs;

disp('Final position (x2):');
disp(x2);

```