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REVIEW PAPERS

A survey related to current technologies in Arctic region for autonomous driving

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Abstract Autonomous driving has sparked an entire revolution in the vehicle sector, offering to increase the safety for road users, productivity, and convenience. However, using autonomous driving vehicles in hostile environments like the Arctic present's challenges because of the bad weather, lack of infrastructure, rough terrain, poor vision, icy and unreliable road surfaces, and inaccessible locations. The paper discuses key technical elements such as sensor systems, data fusion techniques, localization methods, perception algorithms (object detection, scene understanding), decision-making frameworks, and vehicle control mechanisms that are required for autonomous driving in the Arctic. The study focuses on how these innovations could be enhanced and changed to address the specific issues that the Arctic faces. It also highlights on-going academic and business research and development initiatives, showcasing innovations used to overcome difficulties specific to the Arctic. This paper provides great insight for researchers, decision-makers, and professionals interested in incorporating autonomous driving systems under extreme weather conditions. It enables deeper understanding of the difficulties and opportunities specific to the Arctic region, encouraging cooperation and creativity in the search for reliable and effective autonomous mobility solutions.

Keywords Autonomous vechicle · Arctic region · Technologies · Limitaions · Simulators

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1 Introduction

Anticipated as the upcoming significant leap, self-driving cars have the potential to decrease collision occurrences and ease the burden on drivers (Fujii and Shiobara 1971; Kockelman et al 2014). Overcoming the technological obstacles linked to autonomous vehicles in diverse scenarios like adverse weather conditions remains a prominent challenge. It's projected that autonomous vehicles could constitute around 40% of total kilometers journeyed across European nations by 2030 (Five trends transforming the Automotive Industry 2023). Additionally, beyond 2040, most new car purchases in city regions of the United States might be attributed to shared self-driving vehicles, reaching over 70%. There is a significant problem for the commercial deployment of self-driving automobiles, as more technological advancements are required before practical autonomous public vehicles can form the basis for sustainable transport and innovative mobility services. The deployment of self-driving cars can reduce traffic, make roads safer, reduce parking and travel costs (Fagnant and Kockelman 2015).

Many forecasts concerning the applications of self-driving automobiles have been made. As, there is a psychological obstacle in adapting autonomous vehicles. The most potential drawbacks are increased infrastructure, vehicle costs, security issues in specific situations (such as system errors, etc.), and potentially poor job prospects (López-Lambas and Alonso 2019). The knowledge and desires of passengers need to be improved in the advancement of autonomous vehicle technology. Merely 10% of individuals in the United States express confidence in feeling more secure while operating a self-driving vehicle, juxtaposed with 78% who admit to harboring apprehensions about such a prospect (Hands Off Not Quite. 2023; Yang and Coughlin 2014). In the UK, France, Germany, Norway, and Spain, over 80 percent of the people are reluctant to entrust their loved ones to technology (Phinnemore et al. 2021). An experiment in Berlin-Schoenberg, Germany, underscores the sway of factors like functionality, user-friendliness, and societal implications on the acceptability and integration of autonomous vehicles within public transportation systems (Merat et al. 2017). Most consumers in Finland favor testing and using autonomous vehicles if reliability and safety can be ensured (Liljamo et al. 2018).

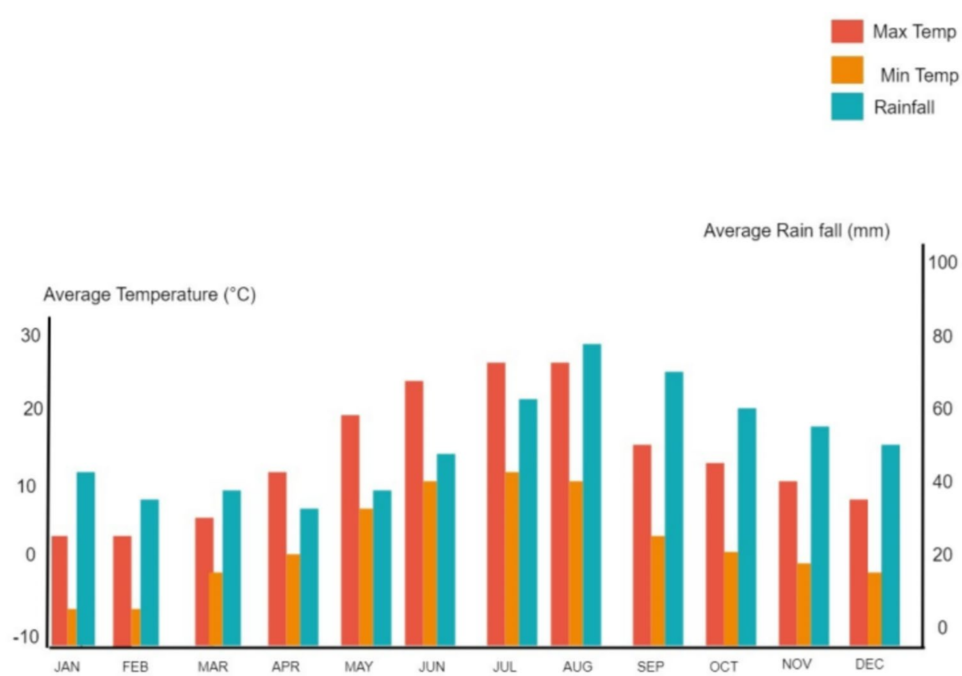
Methods based on prior knowledge are good techniques for creating reliable and flexible systems under complex conditions. Therefore, the International Society of Automotive Engineers (SAE) often creates perception and decision systems based on digital maps (Woodward and Klieštik 2021). Building a robust identification system considering severe weather is another significant challenge (Yoneda et al. 2019). Difficult and severe weather conditions encountered in typical driving situations include rain, sun, snow, and fog. Therefore, it is essential to design reliable decision-making and recognition systems for such situations because each sensor of an autonomous vehicle has its strengths and weaknesses in various environmental conditions.

The Arctic's weather is erratic, with significant seasonal variations (as depicted in Fig. 1) and lengthy, bitter winters. This makes it difficult for road transportation to operate and maintain, as well as in terms of traffic volume, travel times, risks, and ecological effects. Due to its geographical features, including high mountains, deep fjords, lakes, and rivers, several Norwegian highways are particularly vulnerable to bad weather. In general, inconvenience, and risk affect shipping costs and volumes. The accessibility and high expense of alternate routes and ways of transport, the kind and number of cargo, and challenges with operation and maintenance are additional factors that affect the cost of shipping and volumes.

Major issues related to the maintenance and operation of Arctic highways include the maintenance of open roads and highways, controlling emissions from machinery being serviced, and the effects of chemicals on the air, the soil, and water. On icy and snowy roads, a lower average speed increases travel time and fuel consumption. The chance of a crash resulting in damage or even death is significantly raised by poorly maintained and bad cars, in addition to the pollution in the air brought on by higher consumption of fuel and CO2 emissions.

We will now briefly outline the sections in the paper. Section 2 will discuss different Technologies for Autonomous vehicles. Section 3 will give a detailed review of Simultaneous localization and mapping (SLAM). Section 4 discusses different Open-Source Simulators used for Autonomous Driving in different weather conditions. Section 5 will cover the current commercial market of autonomous vehicles. Section 6 will introduce the public datasets available for autonomous driving in normal and Arctic weather conditions. Section 7 will highlight the Limitations and Technological requirements in the Arctic Region. By the end of this paper, the reader will know the distinct challenges involved in autonomous vehicles, as well as the fundamental technologies that constitute them.

Fig. 1 Average Temperature of Arctic



2 Technologies for autonomous vehicle

Actuators, sensors, and processors are the three main parts of the hardware system of autonomous driving cars (Kato et al. 2015; Lim et al. 2019). The ability of self-driving cars to do physical activities like steering, speeding up, and braking is made possible by the actuators, which are essential components of the technology. Actuators are crucial for the accurate and safe management of the automobile in response to various road conditions and driving scenarios. Electric motors are among the actuators because they transform electrical power into mechanical power, which powers each vehicle wheel. With their help, self-driving cars can be stopped or only slightly slowed down by their braking system, which applies pressure to the wheels. Self-driving automobiles also use actuators in their driving capabilities to control the vehicle's movement. Electric power steering (EPS) is recommended for autonomous automobiles because it offers better control and reliability than typical hydraulic systems. Self-driving automobile suspension systems can also utilize actuators to adapt the height and strength of the vehicle's settlement in reaction to road conditions.

Understanding the surrounding environment and anticipating potential changes is critical, as self-driving cars use onboard sensors, including cameras, Light Detection and Ranging(lidar), radar, odometry, and ultrasonic sensors; these are used to recognize their surroundings and make situational judgments based on that recognition. Drivers must also be able to recognize road features such as traffic lights so that the car can function properly in various traffic conditions. Path planning is the next technology (Campbell et al. 2020).

The GPS is primarily utilized in autonomous for adaptation, directions, and maps. GPS can give precise real-time location information for self-driving cars to operate safely and effectively. Self-driving automobiles are capable of accurately identifying themselves on the route and driving to the planned place by fusing GPS data with information from other sensors, including LiDAR and cameras. Self-driving cars can select the best route based on the current situation using GPS to offer live traffic and roadway conditions information. The travel duration can be shortened, and the effectiveness of the public transport system increases as a result. Numerous self-driving vehicles employ HD maps on all kinds of roadways, including city streets. Digital maps' high degree of precision and the diversity of data that may be recorded lower the level of skill needed for autonomous driving. On the other hand, using onboard sensors to determine the location of the auto on a map with excellent precision is always crucial for better usage of HD maps. This ought to be correct to the closest decimeter in most cases. Another method is environmental scouting (Dong et al. 2010).

By integrating automatic localization, knowledge of the environment, and recognition results from digital cartographic data, the vehicle's behavior must be planned in real-time by the central computer of the self-driving car. These three technologies were created for mobile robots (Ge and Cui 2000).

2.1 Vehicle positioning technology

It is important to effectively use maps to estimate vehicle positions accurately. The Global Navigation Satellite System (GNSS) was often used to determine one's position. Although the GNSS can measure position, it isn't easy to use for automatic driving. For example, accurate location determination in urban environments filled with tall buildings is difficult due to the multipath effects of GNSS signals. It is also impossible to pinpoint the position due to the lack of signal from satellites within the tunnel. Thus, it is essential to determine the car's location on a map in actual time (Borenstein et al. 1997; https://www.wired.com/2015/04/cost-of-sensors-autonomous-cars/).

Many studies have used map-matching techniques between digital reference maps and sensor observations for self-localization. The reference map contains precise location information of sensor feature information around the highway. Three different map structures (2D image map, structured vector map, and 3D point cloud map) are commonly used as predefined maps. The 3D point cloud details 3D features around the highway. Although they are low maintenance, these maps are data intensive. Extract pavement features from 3D point clouds and convert them into 2D map images. Therefore, the data size is smaller than that of a 3D map. The vector map contains polynomial curves for curbs, white lines, and other lane and road boundaries.

Due to the sensor's high measurement accuracy and resistance to daily fluctuations, LiDAR-based technologies with decimeter accuracy are being explored. Related publications describe map-matching techniques, including histogram filters (Levinson and Thrun 2010) and sweep matching (Yoneda et al. 2015; Akai et al. 2017), which typically use road paint and map buildings along the road. Vehicles are used as waypoints to estimate the position of the vehicle. Some camera-based techniques have also been proposed to transfer imagery observations to 3D LiDAR maps (Wolcott and Eustice 2014; Xu et al. 2017). On the other hand, self-location techniques based on non-LiDAR maps have also been considered (Ziegler, et al. 2014). Some techniques estimate positions using reference maps from images or MWR features (Schuster et al. 2016; Park et al. 2016). But currently, location results are less accurate than LiDAR-based methods. Choose an appropriate method based on driving conditions, sensor characteristics, and required accuracy.

2.2 Environmental sensing technology

To execute current detection in the object identification environment, road components like traffic signals and related obstructions and traffic users like vehicles, pedestrians, and bikes must use in-vehicle sensors. It is crucial to recognize the road components when traveling on the road to follow traffic laws. By recording this information in advance on a digital map, static road features such as speed limits and stop lines can be identified without looking. Still, it must also recognize dynamic road features such as traffic lights in real-time.

Therefore, when crossing an intersection, the traffic light is one of the most important dynamic elements of the road. Because it is important to classify lighting colors, only color cameras can detect traffic lights. Visiting traffic lights more than 100 m away is important for navigating intersections. A map-based detection method has been proposed in related works (Fairfield and Urmson 2011; Levinson et al. 2011; John et al. 2015).

Basic traffic light shapes, circular features (Omachi and Omachi 2009; Yoneda et al. 2016), and recognition methods using DNNs have all been published. Accurate measurement accuracy is required for the vehicle to perceive static obstacles. Long-range sensors like LiDAR, stereo cameras, and MWR are usually used to find nearby obstacles. The occupancy grid map is constructed as a static 2D or 3D obstacle map with free space, processed as a time series using a binary Bayesian filter to limit the impact of transient false detections.

Additionally, classification is performed by machine learning to identify nearby traffic participants using image data and object shapes learned from remote sensors as input features. When a remote sensor recognizes an object, its views are merged, and the class of the object is determined by machine learning techniques, such as Ad-boost and Support Vector Machine (SVM), which depend on the characteristics of each object (Spinello et al. 2010; Teichman et al. 2011; Irfan et al. 2021). When the object is only a few tens of meters away, a dense observation point cloud can be obtained to confirm the exact shape of the object. The problem is that the generated point cloud needs to be sparser, making it difficult to collect accurate shape data from distant objects.

Compared with lidar, using camera images for reconnaissance can obtain rich observation information, and objects beyond 100 m can be distinguished by using a suitable lens. Since GPU-based acceleration became possible (Liu, et al. 2016; Redmon and Farhadi 2018), deep neural network (DNN)-based recognition has recently emerged as a high-quality camera-based recognition method accuracy. However, since these algorithms can produce rectangular bounding cache detections in images, it is difficult to directly determine the distance of objects. Therefore, the distance information must be determined by sensor fusion using stereo cameras or other distance sensors to determine the relative position of the detected object.

Typically, probabilistic methods such as particle filters or Kalman filters are used to estimate the state of nearby objects. Distance sensors, namely LiDAR, MWR, and stereo cameras, estimate the distance to objects (Granström et al. 2016). In addition, techniques using a single camera (Kuramoto et al. 2018) have also been proposed. Robust recognition of objects is possible with a single sensor and when a variety of sensor systems are coupled.

The geometry of the route and its connection information can be utilized to forecast how a component will act within seconds and identify the object's current motion state. Additionally, it is possible to forecast more appropriate behaviors by considering the development of traffic regulations and the interactions between neighboring traffic actors (Schulz et al. 2018).

2.3 Path planning techniques

Decision-making for autonomous driving requires three different contextual judgments. The first technology is route planning. They are normal car navigation systems, etc., but they need to find the route from the current location to the destination at the track level. Dynamic programming can be used to find paths along intersections in environments where traffic information from digital maps exists. If there is no explicit route information, such as parking or large areas (Dolgov et al. 2023; Likhachev et al. 2023; Do et al. 2013), an optimal route must be found from the drivable area. The second technique is transportation-based trip planning. It is important to observe traffic rules when using this route. Considering the recognition results of traffic light status, stop line position and the position relationship of incoming vehicles and pedestrians at the intersection, it is particularly important to ensure safety procedures when making traffic decisions at intersections. The distance priority relationship between the current and destination routes is also important. Therefore, assessing the situation while managing the route rationally is crucial in this traffic situation. Trajectory optimization is the third technique. Path planning is performed for discovered routes, to find the cheapest and collision-free paths (Werling et al. 2010). Polynomial functions are used in road planning to produce smooth roads and reduce acceleration (bumps), gross driving behaviors, including distance control and speed maintenance, were characterized in a previous study (Tehrani et al. 2013). Designing driving behavior on public roads as a decision-making model will enable flexible, autonomous driving. In theory, these trajectory generation methods guarantee the consistency and regularity of the trajectories selected using polynomial functions. On the other hand, DNNs have been studied and used to propose machine learning-based methods to create control assignments (Bojarski, et al. 2016) or trajectories (Bansal et al. 2018). The input data includes multidimensional information, such as camera images or the location of nearby objects. The neural network can then provide the drive output behavior, such as smooth acceleration. DNN can be deployed in various situations as it can acquire adaptive behavior through machine learning. However, since learning behaviors such as following while driving is still very simple and primitive, it is necessary to use a rule-based approach to create the learning model.

2.4 Hardware and software interfacing

Besides physically installing sensors, ensuring their accurate calibration and alignment is important. This process involves fine-tuning the sensor's position or orientation to maximize effectiveness. Notably, determining the optimal arrangement of sensors on an autonomous vehicle is a multifaceted and iterative undertaking that demands meticulous evaluation of variables such as sensor category, vehicle configuration, and prevailing surroundings. Figure 2 illustrates the strategic sensor layout of an autonomous vehicle. Engineers and designers could employ computer simulations and practical assessments to refine sensor placement, guaranteeing their intended functionality.

Vehicles should be able to discern objects coming from diverse directions when driving in cities, such as pedestrians on zebra crossings, approaching cars at crosswalks, and cars coming from behind in neighboring lanes. To seeing objects from all angles, the layout of the sensor must be considered. A robust system should cover the viewing area with many sensors to assess particularly important locations. To make the right decisions in each situation, autonomous driving systems must also evaluate large amounts of sensor data in real-time (Seif and Hu 2016).

The sensors integrated into autonomous vehicles collaborate harmoniously to offer a holistic perspective of the vehicle's surroundings. This integration, termed sensor fusion, amalgamates data from diverse sensors to construct a more precise depiction of the vehicle's environment. Typically, an onboard computer processes this sensor data, employing machine-learning algorithms and rule-based mechanisms to formulate decisions.

Large databases of actual driving events are used to train these algorithms, teaching the car how to respond in various circumstances. One of the most important duties carried out by sensors in autonomous vehicles is determining the position and direction of the vehicle. For this, inertial measurement units (IMUs), GPS, and wheel encoders are typically combined (Fadadu, et al. 2022). While IMUs and wheel translators provide more accurate measures of the vehicle's movement, GPS only provides a general indication of the vehicle's position. Sensors are used to identify and categorize things in the vehicle's environment, location, and orientation. Cameras are frequently employed to detect other vehicles, people on the street, and traffic signals. LIDAR sensors employ laser beams to create a 3D map of the environment that may be used to estimate object distance and position. Radar sensors can function in poor lighting or inclement weather and are used to measure an object's distance, speed, and direction. The software algorithms of the vehicle use that data to decide the best course of action once entities have been recognized. For instance, the software may apply brakes to prevent an accident if an individual is seen across the road directly in front of the car.

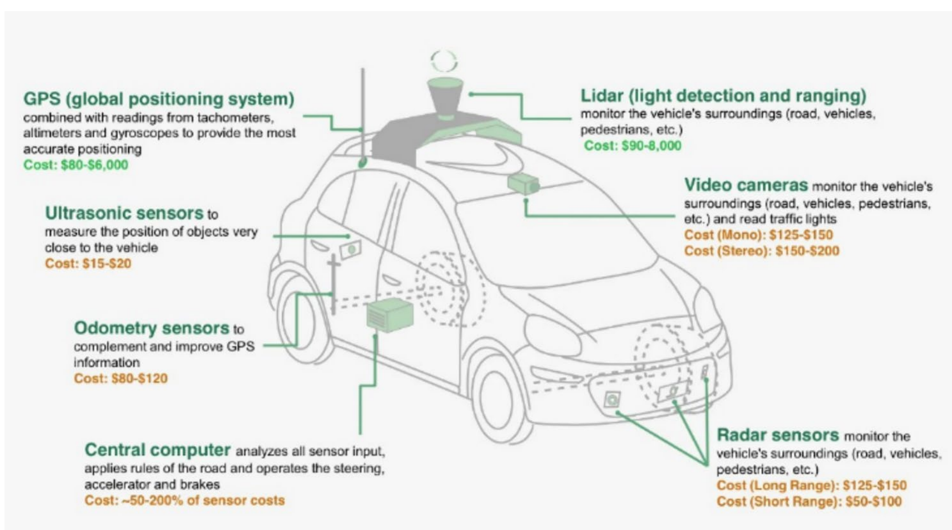


Fig. 2 Mounting of Sensors in Autonomous Vehicle (Qin et al. 2020)

3 Review on simultaneous localization and mapping (SLAM)

SLAM (Simultaneous Localization and Mapping) is a key problem in robotics, computer vision, and autonomous navigation. It involves estimating a robot's pose (position and orientation) in an unknown environment while simultaneously constructing a map of that environment (Kumar et al. 2022). SLAM is crucial for various robotics applications like autonomous vehicles, drones, and mobile robots, enabling autonomous navigation in unfamiliar environments.

The challenge of SLAM lies in real-time pose estimation and map building, accounting for uncertainty from sensor noise, odometry errors, and moving objects. As an active research area, SLAM continually addresses its limitations. Deep learning-based SLAM has emerged as a recent trend, utilizing neural networks to learn mapping and localization functions directly from sensor data. This approach has shown promising results, particularly in complex environments where traditional SLAM algorithms face difficulties. SLAM is critical in autonomous driving systems, facilitating real-time navigation and localization in dynamic and unknown environments. It enables vehicles to detect and avoid obstacles, plan safe trajectories, and operate efficiently in complex traffic scenarios. Reliable and accurate SLAM algorithms are essential for autonomous vehicles to build and update maps while estimating their pose. This capability is vital for safe and effective operation on urban streets, highways, and rural roads. Autonomous driving demands the presence of robust, precise, and streamlined SLAM algorithms capable of operating in real time with minimal latency and exceptional accuracy. Dedicated SLAM algorithms have emerged to cater to the unique requirements of autonomous driving. These encompass visual SLAM, lidar SLAM, and sensor data integration through sensor fusion SLAM. These algorithms employ sensor fusion techniques and deep learning models to accurately estimate the vehicle's pose and map the environment (Jiang, et al. 2022). Table 1. gives a comparative analysis of different types of SLAMs along with their pros and cons.

3.1 Visual SLAM

Visual SLAM (Kolhatkar and Wagle 2021) involves using cameras and image processing techniques to estimate the 3D structure of the environment and the camera's pose. The

Table 1 Comparative Analysis on different types of SLAM

Method	Pros	Cons	Suitable for
Visual SLAM Kolhatkar and Wagle (2021)	1) Provide real-time estimations 2) Creating a map of the environment 3) improved navigation	1) limited range of cameras 2) sensitivity to changes in lighting conditions 3) vulnerability to occlusions high computational requirements	An environment with visual features that can be easily tracked and detected by the algorithm
Lidar SLAM Silveira et al. (2008)	1) high accuracy and robustness 2) navigate and avoid obstacles quickly and efficiently 3) require minimal maintenance 4) work well in a variety of lighting conditions	1) Can be expensive 2) have limited range and visibility 3) vulnerable to certain weather conditions, such as rain, snow, and fog	The environment with complex structures or features, such as urban environments or indoor spaces
Sensor Fusion SLAM (Wei et al. 2021)	1) Cost-Effective 2) Better perception 3) Improved Accuracy	1) Complex Calibration 2) Hardware Limitations 3) Data synchronization 4) Computational requirements	Environments where the available sensors can complement each other to provide a more complete understanding of the environment
Feature based SLAMYeong et al. (2021)	1) Can handle sparse features 2) Can be computationally efficient • Can handle partial observability	1) Limited by the quality of feature extraction • Susceptible to noise	Environments with distinct features (e.g., indoor settings)
EKF SLAM Westman et al. (2018)	1) Can handle nonlinear sensor models 2) Can be computationally efficient • Can handle sparse observations	1) Requires linearization of the system • Assumes Gaussian noise and error distributions	Environments with nonlinear motion
PF SLAM Saman and Lotfy (2016)	1) Can handle nonlinear sensor models and non-Gaussian noise 2) Can handle ambiguous sensor data 3) Can handle multi-modal distributions	1) Computationally expensive • Can suffer from particle degeneracy	Environments with high uncertainty or nonlinear motion

procedure first requires identifying and tracking elements in the camera images to determine the camera's velocity and the environment's 3D structure. Visual SLAM benefits from being portable and affordable because all it needs is a camera, but it could be reactive to changes in illumination and have trouble in situations with little roughness.

The technology of visual SLAM has proven crucial for autonomous driving. By utilizing data from cameras installed on the vehicle, visual Simultaneous Localization and Mapping (SLAM) enables the vehicle to precisely determine its real-time position and orientation while constructing a comprehensive map of its nearby surroundings. Visual SLAM is commonly employed in autonomous driving scenarios alongside additional sensors like LIDAR, radar, and GPS. This combination ensures a resilient and precise vehicle position and orientation estimation. Visual SLAM can be effectively applied with diverse camera types, including monocular, stereo, or RGB-D cameras, tailoring its usage to the specific demands of each application. The structure of Visual SLAM consists of six parts, including a camera module, Feature detection, Feature Tracking, Mapping, Loop Closure, and Optimization, as shown in Fig. 3. The camera module collects image data; the second step is to detect key features in the camera images, such as corners, edges, or key points, that can be tracked over time. This can be done using various feature detection algorithms such as Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features(SURF), Oriented FAST and Rotated BRIEF (ORB), or Features from Accelerated Segment Test (FAST). The next step is to track the detected features over time as the camera moves, using feature tracking algorithms such as KLT, Lucas-Kanade, or optical flow. This permits estimation of the camera's motion by analyzing alterations in the positions of the monitored attributes across sequential frames. Leveraging these tracked attributes, it becomes possible to gauge the three-dimensional arrangement of the surroundings by calculating the triangulated positions of these attributes in 3D space. These approximated 3D coordinates then facilitate the development of an environment map. However, with time, inaccuracies might accrue in the projections of the camera's path and the configuration of the environment's three-dimensional structure. Loop closure detects when the camera revisits a previously visited location in the environment and uses this information to correct the accumulated errors in the estimates. Once the camera's trajectory and the 3D structure of the environment have been estimated, the estimates can be refined using optimization techniques such as bundle adjustment or SLAM back-end optimization (SumikuraShinya and SakuradaKen 2022).

3.2 Lidar SLAM

Light-detection and Ranging technology is used in Lidar SLAM (Silveira et al. 2008). A scanning laser or lidar sensor is used in lidar SLAM to construct a 3-D cloud of points of the surroundings by measuring the distances to various objects in the environment. The Lidar SLAM system works by iteratively analyzing lidar data that the robot gathers around the environment. The algorithm compares the most recent lidar scan to determine the robot's orientation in the map to earlier scans. It then recognizes features in the lidar data, such as angles and edges, and compares them to features on the map that have already been recognized. The map is then updated, and the feature correspondences are used to estimate the robot's pose more precisely. The Lidar SLAM algorithm calculates the robot's pose and the map using a probabilistic approach. Using the sensor data, it maps and updates a probability distribution over the range of potential positions. To update the probability distributions, the algorithm uses methods from Bayesian filtering, such as the Kalman filter or the particle filter.

Numerous real-world uses exist for lidar SLAM, including in drones, mobile robotics, and autonomous vehicles. It makes it possible for these systems to map and navigate their surroundings with high precision and dependability. In contexts with intricate features or structures, such as urban settings or enclosed areas, lidar SLAM is very helpful (Khan et al. 2021).

Lidar SLAM is used by autonomous cars to create and update maps of their surroundings, including the geometry of the roads, obstructions, and other characteristics. The vehicle can recognize and identify objects, such as other

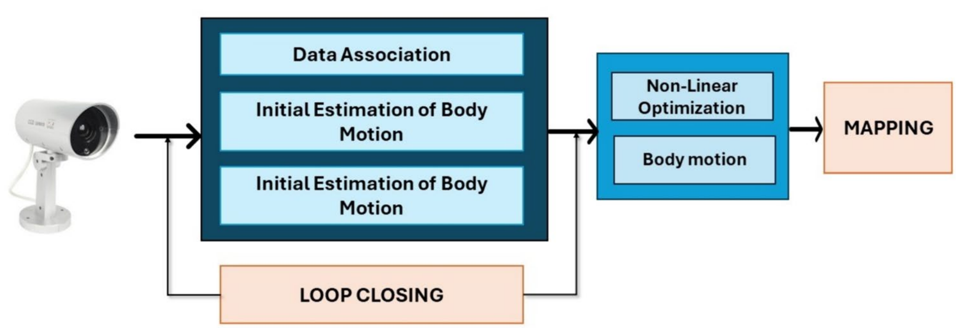


Fig. 3 Structure of Visual SLAM

automobiles, pedestrians, and bicycles, and respond appropriately, thanks to the Lidar SLAM algorithm. An autonomous vehicle, for instance, can spot someone walking across the roadway and safely steer clear of them. The car can precisely identify and position itself in the environment thanks to the high-quality point cloud produced by the Lidar sensor, and the SLAM algorithm permits it to change its map as it drives through the environment. Additionally, Lidar SLAM can be used with other sensor methods, including cameras and radar, to offer the autonomous vehicle a more reliable perception system. To create a more precise and thorough understanding of the surroundings, sensor fusion technologies can combine input from many sensors, allowing the vehicle to make more educated judgments about its course of action. As depicted in Fig. 4, the following components make up the Lidar SLAM structure.

- Lidar sensor: A lidar sensor is the main device for gathering 3D data about the surroundings. It emits laser beams and clocks the amount of time needed for the beam to return after being reflected off an environmental object.
- Odometry: It is employed to monitor the lidar sensor's motion. Based on the sensor's prior movement and velocity, it is a technique for determining the sensor's positioning and orientation.
- Mapping: This is the procedure for creating an environment map using the information gathered by the lidar device. This is accomplished by using algorithms that transform the lidar data into a point-cloud-like representation of the surrounding area.
- Localization: This is the process of determining the current location of the lidar sensor in relation to its surroundings. To do this, the received lidar data and the previously created map are compared, and the sensor's position is inferred from the intersection of the two.
- SLAM: To simultaneously map the surroundings and determine the location of the lidar sensor, mapping and localization are combined in real-time. Algorithms that maximize the prediction of the sensor's placement and the map-making process are used to achieve this.

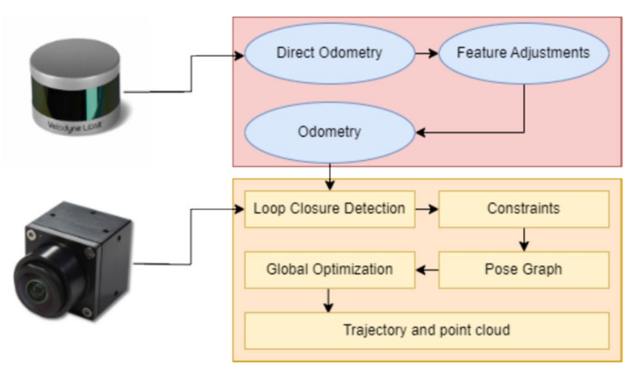


Fig. 4 Structure of LIDAR SLAM

3.3 Sensor fusion SLAM

Sensor fusion is a crucial piece of technology that enables self-driving cars to effectively perceive and navigate their surroundings (Wei et al. 2021). Sensor fusion combines data from various sensors to increase environmental knowledge's precision, resilience, and comprehensiveness. Technically speaking, sensor fusion combines information from many sensor types, including optical, depth, inertial, and LiDAR devices, to produce a more complete picture of the environment. This entails creating algorithms that can effectively combine various data kinds to reduce errors and optimize the knowledge acquired. Sensor fusion calls for specialized hardware to gather and interpret the data and precisely align and sync data from several sensors. Additionally, sensor fusion methods may be computationally demanding, necessitating high-performance computer infrastructure to handle the massive amounts of data produced by numerous sensors. Despite these technical obstacles, combining sensors has the power to change various applications, from robotics to autonomous vehicles, by supplying more precise, resilient, and comprehensive data about the environment.

3.4 Feature based SLAM

Using distinguishing environmental cues, such as edges or corners, feature-based SLAM (Yeong et al. 2021) calculates the robot's pose and maps the surrounding area. Techniques like the SIFT or the Harris corner detector are frequently used. Once features have been identified, they are compared between various frames to ascertain the robot's motion and modify the map. The Fast SLAM algorithms and the EKF-based SLAM system are the two most often used algorithms for feature-based SLAM. SLAM is computationally efficient and effective in surroundings with distinct characteristics based on features. Still, it can be challenging in environments with no features or while the features are unstable or difficult to detect.

In self-driving instances where the environment provides distinguishing features, such as lane lines, traffic signs, and buildings, feature-based SLAMs can be helpful. A high-precision map of surroundings can be made using feature-based SLAM, which can be applied to tasks like localization path planning and preventing obstacles. The sensors frequently found in autonomous cars, including cameras, lidar, and radar, can execute feature-based SLAM.

3.5 Extended kalman filter (EKF) SLAM

The EKF algorithm, a recursive estimating method that defines a non-linear framework and modifies it using the Kalman filter, estimates the robot's pose and the location map of the surrounding area in the EKF SLAM (Westman et al. 2018). Building an environment map with EKF SLAM entails using information from sensors like odometry, laser distance finders, or cameras. The Fast SLAM technique and the EKF-based SLAM algorithm are the two most often used EKF SLAM algorithms. A tried-and-true method with a large user base, EKF SLAM can deal with non-linear systems and be computationally effective. However, it may require careful adjustment of the sensor noise values because of linearization imperfections.

When a robot moves in a non-linear setting with a highly dynamic environment, EKF SLAM can be helpful. For purposes including the localization of operations planning of paths and obstacle avoidance, EKF SLAM can be utilized for estimating the robot's pose and a geographical representation of the surrounding area. Many sensors, such as cameras, lidar, radar, or GPS, can accomplish EKF SLAM.

3.6 Particle filter (PF) SLAM

PF SLAM (Saman and Lotfy 2016) uses a collection of particles, each of which stands for a potential theory, to represent the pose of the robot and the map of its surroundings. The particles are transmitted over time using a motion model and updated based on data from sensors like odometry, distance finders, or cameras. The two most often utilized PF SLAM algorithms are the Fast SLAM technique and the Rao-Blackwellized particles filter. Although PF SLAM is a reliable method that can deal with non-linear systems and ambiguous measurements, it can be computationally challenging and may necessitate careful particle parameter tweaking.

By calculating the location and orientation of the vehicle while mapping the environment, PF SLAM is essential to autonomous vehicles. This method precisely locates the car and recognizes landmarks by fusing data collected by sensors from systems like GPS, lidar, or camera with motion information. PF SLAM is an important tool for developing effective and safe autonomous driving because of its adaptability to changing situations and compatibility with navigational and control systems.

4 Open-source simulators for autonomous driving

According to the application and requirements, several open-source simulators can be utilized in an autonomous vehicle because they are accessible for varied weather situations. Various simulators can be used to test and develop self-driving systems in various environmental settings. A comparison of a few of the open-source simulators is provided in Table 2. These simulators can create and test autonomous driving systems, ensuring their dependability and safety under difficult circumstances.

4.1 Carmaker

A complex software platform called a CarMaker (Tang et al. 2014) maker simulator created specifically for autonomous driving offers an organized virtual environment for designing, testing, and improving autonomous vehicles and the systems that go with them. Engineers, designers, and researchers can design, verify, and improve autonomous driving techniques and systems using this simulator without the requirement for actual field testing. Users can specify alternative scenarios, highway conditions, patterns of traffic, and environmental issues within the simulator to assess how autonomous vehicles perform in various situations. It enables experimentation of perception, decision-making processes, and control algorithms by simulating data collected from lidar, cameras, radar, and other sensors. The simulator shortens the development cycle and helps improve the safety, effectiveness, and durability of self-driving technology before it is used on public roads by simulating real-world driving scenarios, such as complex urban environments, bad weather, and even rare edge cases.

4.2 Vortex studio

For simulating intricate connections among vehicles and their surroundings, such as topography, the climate, and other objects, especially those seen in the Arctic region, use Vortex Studio (Rong 2020). The software enables users to evaluate numerous situations, such as vehicle handling, strength, and performance, in various weather circumstances. It can mimic various types of vehicles, including cars, trucks, and heavy equipment. Vortex Studio is the perfect tool for building and testing new assistance technologies and self-driving systems since it offers a complete simulation environment with physics engines, realistic car models, and cutting-edge visualization capabilities.

4.3 SCANeR

A state-of-the-art simulator called SCANeR (Matsumoto, et al. 2020) was created exclusively for creating, evaluating, and testing technologies for self-driving vehicles. SCANeR, created by AVSimulation, offers engineers, scholars, and developers a thorough and incredibly realistic virtual environment to evaluate self-driving systems' effectiveness, safety, and dependability. One of its distinguishing features is SCANeR's capacity to generate intricate and complex traffic scenarios, enabling users to mimic interactions with other automobiles, pedestrians, and cyclists. This capacity is essential to evaluate perception, decision-making, control algorithms, and examine how autonomous vehicles respond to unforeseen circumstances on actual roads.

4.4 VIRES VTD

The VIRES VTD (Champion et al. xxxx) simulation platform is designed to replicate a diverse range of driving scenarios, encompassing conditions frequently encountered in Arctic regions, such as snowy terrain, icy surfaces, and reduced visibility. This software empowers users to thoroughly assess various vehicle categories across various distinctive driving situations, ranging from cars and trucks to buses. It can mimic a variety of environmental circumstances, including diverse surface types and weather conditions. VIRES VTD is the perfect tool for developing and testing new assistance technologies and self-driving systems since it offers a complete simulation environment that includes realistic car models, physics engines, and cutting-edge visualization capabilities.

5 Technology and innovations in autonomous vehicle by different companies

With numerous companies investing in R&D to raise the reliability and security of automated vehicles, the technological sectors relating to automated vehicles have advanced significantly over the past two decades. These are a few instances of cutting-edge innovation and advancements in driverless cars from a few of the top global brands. Table 3. shows the comparison of these companies.

5.1 Waymo (Alphabet subsidiary)

Waymo (Gangel et al. 2021) Since 2009, a division of Alphabet Inc., has been working on autopilot systems. The sensors that Waymo's autonomous vehicles utilize to sense their surroundings consist of lidar, laser radar detectors, and cameras. Waymo's predictive techniques employ machine learning methods to forecast other drivers' actions by analyzing their driving patterns and paths. This enables the car to recognize possible threats and react accordingly. Waymo's navigation techniques employ algorithmic learning to ascertain the best route for the car, considering variables like weather, traffic, and road conditions. Waymo used a specially designed computer simulation environment named "Carcraft" to test and evaluate its autonomous vehicle techniques in a virtualized scenario. Carcraft is not the only simulator and tool that Waymo employs for assessment and

Table 2 Features and Sensors in different Simulators

Simulator	Sensors	Environment features	Other features
CarMakerTang et al. (2014)	lidar, radar, camera, and GPS	snow, ice, low visibility, and temperature changes, customizable road network	real-time simulation and hardware-in-the-loop testing, customizable vehicle model, and physics engine
Vortex Studio Rong (2020)	lidar, radar, camera, and GPS	snow, ice, wind, complex terrain, and precipitation	real-time simulation and hardware-in-the-loop testing, a wide range of simulation tools, including a scenario editor and a motion platform interface
SCANeR Matsumoto, et al. (2020)	lidar, radar, camera, and GPS	snow, ice, low visibility, temperature changes, customizable road network, and environmental conditions	real-time simulation and hardware-in-the-loop testing, scenario editor, and a wide range of simulation tools, including a physics engine and a vehicle model editor
VIRES VTD Champion et al. (xxxx)	lidar, radar, camera, and GPS	snow, ice, low visibility, and temperature changes, offer a customizable environment	real-time simulation and hardware-in-the-loop testing, a scenario editor, and a wide range of simulation tools offer a cloud-based simulation platform

Table 3 Comparison of Technologies used by different companies

Company	Sensors	Algorithms	Simulators
Waymo Gangel et al. (2021)	Lidar, Radar, Cameras, GPS	Deep Autonomy, CNNs, LSTM, GNN, A*, D*, MPC	Carcraft, CARLA, Unreal Engine
Tesla Google sibling Waymo launches fully autonomous ride-hailing service. (2023)	Forward-facing Radar, Cameras (provide 360-degree view)	Not Disclosed	Tesla Simulation Environment
Apple Endsley (2017)	Lidar, Radar, Cameras, GPS	Not Disclosed	Not Disclosed
BMW Lyu et al. (2020)	Optical Cameras, Lidar, Radar, HD maps	Not Disclosed	Virtual Test Drive (VTD)
VOLVO Dorrer (2018)	Radar, Cameras, Multi-beam laser, HD 3D maps, High precision GPS	Not Disclosed	Volvo Autonomous Driving Simulator
Baidu Song et al. (2021)	Lidar, Radar, Cameras, GPS	CNNs. RNNs, DDPG	ApolloScape
Uber ATG Tian et al. (2018)	Lidar, Radar, Cameras, GPS, odometry, HD maps	FusionNet, Hector SLAM, Rule-based systems	Carcraft

testing; the CARLA model and the Unreal Engine are two other examples. Waymo's autonomous vehicle can travel on public roadways rather than with assistance from an actual driver. Numerous safeguarding measures, like multiple detectors and controls, invulnerable mechanisms, and alternate power sources, are installed in the vehicle.

5.2 Tesla

Tesla (Google sibling Waymo launches fully autonomous ride-hailing service. 2023) has created Autopilot technology, allowing its cars to drive somewhat autonomously. The business is also working on an FSD system, which will eventually enable autonomous driving. A variety of sensors, like video cameras, radar, ultrasonic devices, and LiDAR, are included in Tesla vehicles. With the help of these sensors, the automobile can perceive everything around it in 360 degrees, which enables it to recognize and follow things like other cars, people walking, and traffic signs. The neural networks that form the foundation of Tesla's autonomous vehicle system are taught on vast data. These artificial neural networks are employed in decision-making processes, navigation, and recognition of objects. The precise machine learning techniques Tesla uses for their self-driving technologies are not publicly known. It is generally accepted that they are utilizing a blend of behavioral and deep learning algorithms to accomplish this. Tesla's cameras can take detailed pictures of the area around the car. Afterward, algorithms based on computer vision are used to analyze these photos to interpret signs for traffic, recognize road signs, and identify anything. The "Tesla Simulation Environment" is a private model that Tesla employs to evaluate and verify its autonomous vehicle system. The Tesla Simulator System can replicate millions of miles of travel in a matter of hours thanks to its highly adaptable design. It permits Tesla to test its autonomous system in various situations, such as intricate junction situations, unfavorable weather, and uncommon extreme circumstances that might be risky or difficult to duplicate.

5.3 Apple

Since about 2014, Apple (Endsley 2017) has focused on developing autonomous vehicle technology, although the development effort has encountered various obstacles and direction changes. Over the past few years, it has been claimed that Apple is now concentrating on creating technologies for autonomous driving that it may utilize in collaboration with other automobile manufacturers rather than producing a fully driverless vehicle. Apple has not made any formal statements about the detectors and AI techniques that go into its autonomous automobiles. On the other hand, speculations and gossip about the technologies that Apple employs have surfaced. There are rumors that Apple's autonomous vehicles use Velodyne lidar detectors. Additionally, cameras have been integrated into Apple's autonomous cars to record visual data about their surroundings. The cameras might be utilized for tracking, identifying, and detecting objects. A different kind of sensor Apple could use in its autonomous vehicles is radar. Given Apple's expertise in machine learning, it seems probable that their automated cars employ a range of ML methods. Employing certain algorithms for perception, judgment, and control is possible. Like other businesses developing autonomous vehicles, Apple is evaluating and confirming its technology through models. It's crucial to remember that Apple has not acknowledged any information on its autonomous vehicle technology. Thus, these features and sensors are based only on rumors. It's conceivable that Apple is using more sophisticated or different technologies than what has been published.

5.4 BMW

Referred to as "BMW iNEXT," BMW's autonomous automobile technology (Lyu et al. 2020) is intended to be a fully autonomous drive mechanism that can assume vehicle control in specific scenarios, such as on a busy road or in congested traffic. The sensor, driving simulator, and techniques of BMW's self-driving auto system likely contain some key features, but the manufacturer still needs to make all its technical data public.

BMW's autonomous vehicles incorporate an array of sensors, encompassing LiDAR, recording apparatuses, radar detection systems, and ultrasonic sensors. This integration endows the car with comprehensive environmental awareness, enabling seamless recognition and tracking of dynamic entities such as fellow vehicles, pedestrians, and traffic signals. BMW tests and validates its self-driving technology on many simulators. The "Virtual Test Drive" (VTD) is one of these simulators that enable BMW to produce lifelike simulations of various driving situations. BMW's cameras capture high-resolution images of the vehicle's surroundings. The algorithms in the automobile get smarter and can forecast outcomes more precisely as they gather more data. The pictures are then processed using computer vision algorithms to identify road markings, read traffic signals, and detect objects. BMW uses a range of decision-making mechanisms to control the vehicle's mobility. When deciding whether to shift tracks, brake, or accelerate, these algorithms analyze information gathered from cameras and sensors. BMW's autonomous driving system will probably be complicated, including extra simulations and algorithms that aren't on the list.

5.5 VOLVO

VOLVO (Dorrer 2018) has been working on developing self-driving car technology for several years. A self-driving car of VOLVO has five integrated sensors: cameras, radar, and ultrasonic sensors. The multi-beam laser provides exceptional vision on a long range of up to 150 m so drivers can see far ahead and be warned of a coming danger. Highly detailed 3D maps and the high-precision GPS (high-accuracy positioning system) are integrated to provide the exact location of the car and the surroundings. The map and GPS also help find the safest and most efficient way. These sensors are utilized for observation and decision-making, offering data on the car's surroundings. While the precise algorithms employed by Volvo remain undisclosed to the public, artificial intelligence and machine learning play significant roles in their automobile technology. Volvo may use localization algorithms to determine the vehicle's position and orientation in the environment. These algorithms use data from GPS, lidar, and other sensors to estimate the vehicle's location. The company has developed a custom simulator called the Volvo Autonomous Driving Simulator, which tests different driving scenarios and trains their ML algorithms. Volvo's self-driving car technology is supported by cloud computing. Utilizing cloud resources for the processing of data, its analysis, and storage enables companies to manage massive volumes of data and use distributed computing capabilities (Pelliccione et al. 2017).

5.6 Baidu

The Chinese tech firm Baidu (Song et al. 2021) is working on autonomous vehicle development with its Apollo subsidiary. These autonomous vehicles sense their environment using a variety of sensors, including lidar, laser radar, cameras, and GPS. They aggregate the data from various sensors using sensor synthesis technology to get a more complete picture of the surroundings. The position and orientation of Baidu's automated cars are ascertained by combining lidar, GPS, and odometry. They employ a localization technique that incorporates information from multiple sources to get a more precise estimation of the car's location. High-definition maps are used by Baidu's self-driving cars to navigate their surroundings. These maps are made and updated using a map system that takes information from the car's travels. In their self-driving cars, Baidu employs various machine learning techniques, such as deep learning algorithms for segmentation by semantics, object identification, and decision-making. They specifically employ reinforced teaching methods, recurrent neural networks, and convolutional neural networks. Enabling the vehicle with the capacity to perceive and respond to its surroundings, these algorithms undergo training using extensive collections of actual driving scenarios. Baidu has harnessed an array of reinforcement learning algorithms, including sophisticated iterations, to empower their self-driving vehicles. Baidu has harnessed an array of reinforcement learning algorithms, including sophisticated iterations, to empower their self-driving vehicles. Baidu has employed several famous algorithms, including Deep Deterministic Policy Gradient (DDPG). Baidu has enhanced the capabilities of its self-driving cars by combining DDPG with additional deep-learning algorithms. For detecting objects and semantic segmentation, they have combined DDPG with convolutional artificial neural networks (CNNs) and RNNs (recurrent neural networks) when making choices. Regarding the simulator, Baidu created ApolloScape, a virtual setting that mimics actual driving environment conditions. In a secure and controlled environment, a simulator like this is used to test and certify the functionality of self-driving vehicles. A collection of resources for data annotations, presentation, and data analysis are also included in Apollo Scape. These tools are crucial for developing and testing the machine algorithm for learning used in self-driving automobiles (China will make rapid progress in autonomous vehicles 2018).

5.7 Uber's advanced technologies group (ATG)

Uber's ATG (Tian et al. 2018) research and development department aims to advance autonomous vehicle technology. Uber ATG's autonomous cars sense their environment using a variety of sensors, such as radar detectors, lidar imaging, and cameras. The information collected from these devices is combined with a deep learning system known as "FusionNet" to produce a 3D model of the surroundings. To make choices, they combine machine learning algorithms with rules-based systems. The automobile's behavior is optimized in various settings with reinforcement learning algorithms. A combination of lidar, odometry, and GPS is employed to ascertain their location and orientation within the surroundings. They blend information from multiple sources using a localization method called "Hector SLAM" to accurately predict the car's location. They use a mapping system that builds and refreshes these maps using information gathered while the automobile is driving. They use "Car craft" for simulation, which enables them to examine their methods in a secure and regulated environment while simulating various driving scenarios (Carvalho 2020).

6 Public datasets available for autonomous driving in Arctic

High-quality data access is necessary to advance and assess autonomous driving technology. Although gathering extensive datasets for research on autonomous driving can be costly and time-consuming, researchers and developers can develop and evaluate their automated drive techniques and methods using several datasets that are freely accessible. These datasets contain annotations for tasks like object identification, tracking, semantic segmentation, and various sensor data types, including LIDAR, cameras, and GPS/IMU. The are various open-source datasets that are available for normal weather conditions including Waymo Open Dataset (Hagman and Lindh 2019), ApolloScape (Mei, et al. 2022), KITTI (Huang, et al. 2018) and Cityscapes (Deschaud 2021). A lot of research has been done on these datasets for autonomous driving in normal weather conditions. Unfortunately, few publicly available datasets exist for autonomous driving in Arctic environments. Most publicly available autonomous driving datasets focus on more common environments, such as urban and suburban areas, and do not include data collected in snow. However, some companies and organizations are working on collecting and releasing datasets for autonomous driving in snowy conditions, including:

6.1 Winterdrive dataset

Researchers at the University of Michigan generated the Winter Drive dataset (Cordts, et al. 2016), which comprises sensor data from a self-driving car operating in ice and snowy in Ann Arbor, Michigan. The United States dataset contains annotations for tasks including object recognition, tracking, and 3D localization, as well as data from various sensors, including lidar, cameras, and GPS. The dataset comprises weather scenarios, such as snow, ice, and slush, and various driving situations, including urban and rural areas. The WinterDrive dataset provides a valuable resource for researchers and developers working on autonomous driving systems for winter conditions. It can be used to evaluate the performance of algorithms for object detection, tracking, and localization in snowy and icy environments, and to develop and test new algorithms specifically designed for these conditions.

The data is stored in a variety of formats, including photos and videos in JPEG, PNG, MP4, or AVI, LiDAR data in.pcd or.bin, radar data in proprietary binary formats, and GPS/IMU data in CSV or JSON. Annotations contain object labels with bounding boxes, as well as segmentation masks for automobiles, people, and road signs in COCO JSON, Pascal VOC XML, and KITTI label formats. Semantic segmentation labels road surfaces and snow covering at the pixel level, typically in PNG masks or JSON files, whereas temporal annotations allow for object tracking across frames.

The dataset's size can reach several terabytes and is separated by weather conditions, time of day, and location to allow for targeted research. It is accessible through academic portals or cloud storage services such as AWS and Google Cloud. All sensor data is synchronized using exact timestamping, which is commonly done with GPS or high-precision clocks. Calibration details, such as intrinsic parameters for camera lenses and LiDAR, as well as extrinsic sensor modifications, are provided to assure precise spatial alignment.

6.2 nuScenes winter dataset

This dataset was created by nuTonomy, a startup acquired by Aptiv in 2017, and consists of over 1,000 driving scenes recorded in urban environments in Boston and Singapore from various autonomous vehicle platforms in winter environments, including snowy conditions. The dataset comprises GPS and IMU metrics, radar, lidar, and excellent-quality camera photos. Tags for object identification, monitoring, and classification are also given. The dataset offers a broad spectrum of city drive circumstances, encompassing driving during the day and at night. They may be employed to evaluate how well autopilot programs function in various environments (Kurup and Bos 2022).

Although these datasets are tailored for self-driving in arctic situations, they are still small and have a narrow focus. Further study and data gathering are required to promote the development of driverless vehicles that can function efficiently in snow.

The collection is thoroughly organized, with photos in JPEG format, LiDAR data in.pcd files, radar data in.pkl files, and GPS/IMU data in CSV files, all synchronized with precise timestamps to assure temporal alignment. Annotations include bounding boxes for things like as vehicles, pedestrians, and bicycles, as well as pixel-level semantic segmentation and object tracking information across frames, allowing for more advanced perception and tracking research.

The nuScenes Winter Dataset contains several terabytes of data and is divided into several scenes, each with 20-s video and related sensor data. This vast amount of high-resolution data is available via the nuScenes website and linked academic platforms, which normally need user registration and compliance to conditions of use.

Sensor data is synchronized using GPS time or high-precision internal clocks, and all sensors are calibrated with detailed intrinsic and extrinsic parameters to ensure accurate spatial alignment. This dataset has a variety of uses, including training and testing perception models in winter settings, improving SLAM techniques, developing robust path planning and control algorithms for icy roads, and producing realistic winter driving scenarios in simulation environments. The nuScenes Winter Dataset is a great resource for improving autonomous driving technology in harsh winter conditions.

7 Limitation and technological requirements in arctic region

The difficulties presented by the topography and climate of the Arctic have substantial effects on self-driving in the area. The emergence of autonomous vehicles holds the potential to revolutionize transportation on various fronts, yet the unique environmental challenges of the Arctic region warrant careful consideration. Notably, melting ice stands as a significant hurdle during the summer months. The sea ice layer that covers much of the Arctic Ocean starts melting as temperatures rise, posing various dangers for people traveling through the area (Bull, et al. 2020). Some examples of these dangers include open sea, which can be hazardous for ships and boats, and ice floes that can change and create impediments. Permafrost, or permanently frozen soil, can also melt throughout the summer, which might cause issues. Permafrost thawing can lead to ground instability, heightening the susceptibility to hazards like landslides. Furthermore, this process risks releasing substantial amounts of methane, a potent greenhouse gas, into the atmosphere, consequently expediting the progression of climate change. Last but not least, Arctic summer storms can also be especially violent, with powerful gusts, copious rain, and even lightning strikes (Iijima et al. 2016).

Navigation presents a significant obstacle for autonomous cars in the Arctic. Vehicle navigation can be challenging in the face of melted ice and moving ice floes. Conventional mapping systems must be more precise and current to offer trustworthy guidance (Reid, et al. 2019). This could be especially troublesome for autonomous cars, which depend largely on precise data from maps to make judgments. The specific sensors and equipment requirements may present another challenge for autonomous vehicles in the Arctic. To safely travel the area, vehicles may need sophisticated sensors to recognize and react to shifting weather conditions, including unexpected storms or blizzards.

Additionally, they could require specialist tires or other tools that can withstand the bitter cold and ice conditions. Additionally, ice in the Arctic may provide difficulties for self-driving cars. As previously indicated, permafrost thawing can make the ground unstable and result in landslides or other dangers. To operate securely in the area, autonomous cars would be required to be able to recognize and steer clear of these dangers (Lima and Victorino 2015).

The harsh winter climate is the major barrier to the localization of autonomous vehicles (AVs) and autonomous driving (AD) uses in northern latitudes. Because of the presence of snow, fog, mist, and darkness, this weather can reduce the efficacy of imaging sensors and harm sensor performance. Due to this weather, the various kinds of detectors used in autonomous driving cars may have particular difficulties. In snowy conditions, cameras may encounter lower vision and contrary, making detecting objects challenging. Lidar sensors may have signal dispersal, absorption, and attenuation problems, which can produce inaccurate results and insufficient information for the perception algorithm. Radar sensors could identify objects in icy conditions but might not be able to classify them, affecting the detection system's accuracy (Koopman and Wagner 2017).

An experiment called the Volvo Vehicles Winter Test (Billones, et al. 2018) was conducted in the Arctic region to gauge how well autonomous vehicles operated in subzero conditions. The test was conducted in northern Sweden, near Arjeplog, in January 2020. The test's autonomous trucks came with various sensors, cameras, and Lidar devices that allowed them to navigate and run independently. The trucks were put through a series of movements on a closed track, including acceleration, braking, and turning. But the harsh Arctic climate, with its snow, ice, and freezing temperatures, posed serious difficulties for self-driving vehicles. The frigid temperatures impacted the batteries' efficiency in the vehicles and the precision of the Lidar observations. The vehicles struggled to maintain stability and traction while navigating the blocked track due to the snow and ice on the ground. The Volvo team created specialized software that could consider the difficult Arctic circumstances to handle these issues. The software could adjust the vehicles' movement and speed to consider the low traction circumstances and maximize battery life in chilly weather.

Additionally, the Volvo team tried to increase the Lidar readings' accuracy by employing stronger lasers that could cut across the snow and ice on the floor. They also created a mechanism that could regularly clean them to prevent ice and snow from building on the Lidar sensors. The Volvo Trucks Snow Test emphasizes the value of testing autonomous cars in difficult terrains like the Arctic to ensure their safe and dependable operation in harsh conditions. The test's findings have assisted Volvo Trucks in further refining their automated driving technology for usage in hostile environments and enhancing the functionality of the many sensors and communications technologies employed in their automated trucks.

Initiated in 2015, the NOAA Arctic Project (Manley and Systems 2003), spearheaded by the National Oceanic and Atmospheric Administration (NOAA), aims to investigate the impact of climate change on Arctic marine ecosystems. This research employs autonomous underwater vehicles (AUVs) equipped with sensors to access data from beneath the ice. The AUVs were made to acquire data from behind the ice by navigating through the difficult Arctic environment autonomously. Low light levels, freezing temperatures, and ice formation that could harm the vehicles were key obstacles the AUVs faced in the Arctic. The NOAA team created specialized navigation algorithms to handle these issues and take into account the harsh Arctic environment. According to the algorithms, the AUVs could move around the ice formations and gather data from below without becoming stuck or hurt. The sonar, acoustic detectors, and cameras that the AUVs were fitted with allowed them to gather information on the biological and physical aspects of the Arctic region. The information gathered by the AUVs was put to use to learn more about how the Arctic's marine ecosystems are being impacted by climate change. The NOAA team had to create specially designed communication technologies to provide dependable communication between the AUVs and the control systems. The severe Arctic environment may impair wireless communications, making it difficult for the AUVs to maintain contact with the control equipment. The NOAA Arctic Project emphasizes the significance of creating specialized sensor technology, communication networks, and navigation algorithms to guarantee self-driving vehicles' safe and dependable operation in harsh Arctic conditions. The experiment shed important light on how climate change affects marine ecosystems and showed how autonomous technology may help scientists gather data in difficult and isolated locations.

Simulation is useful for testing and refining how autonomous cars behave in inclement weather. It allows engineers to simulate various environmental and scenario factors, offering a thorough and effective testing strategy. In contrast to physical testing, simulation doesn't require waiting for real snowfall, and results are accessible virtually instantly. This makes it possible for producers of self-driving cars to create weather-aware self-driving systems more swiftly. Snow presents particular and difficult problems despite modeling successfully forecasting results in extreme conditions like space and the deep sea. The model used for simulation must consider various details to effectively represent the effects of snow, including the size, shape, location, and optical characteristics of each snowflake, as well as the location and form of the snow area on the road surface. By considering these elements, simulation can offer helpful insight into how autonomous vehicles behave in icy circumstances, enhancing their performance and safety.

The potential for autonomous vehicles to revolutionize transportation is evident from a broader perspective. However, realizing their effective utilization in Arctic settings hinges on tackling the distinct challenges of the region's geographical and climatic factors. This endeavor will probably entail substantial dedication toward specialized sensors, cutting-edge mapping technologies, and purpose-built equipment. Furthermore, continuous research and development efforts will be pivotal in accommodating the dynamic environmental changes characteristic of the Arctic.

8 Conclusion

This paper presented the unique challenges that were associated with the deployment of autonomous cars in Arctic regions. Technological limitations associated with deploying autonomous cars in Arctic regions are also discussed. The paper highlights various open-source simulators that can be used for self-driving cars in the Arctic Region. Moreover, public datasets for self-driving cars in the Arctic region are also mentioned. The researchers can use these datasets.

It is impossible to overestimate the significance of autonomous vehicles functioning in all forms of weather and on all types of routes. Advanced solutions and systems are required for autonomous cars to function effectively in good and bad weather. It is also crucial to have timely, accurate operating and safety performance forecasts and data on the state of the roads' weather.

As technology advances solve the difficulties of operating automatic cars in severe weather conditions, the potential use of self-driving automobiles in the Arctic region appears bright. Self-driving cars have the potential to significantly improve mobility in Arctic regions with further research and development, especially in isolated communities with little road infrastructure. The achievement of autonomous cars in Arctic areas will also depend on the regulatory environment and public perception. Organizations and governments must be involved in its development and implementation to guarantee that the system is secure and satisfies the requirements of the Arctic community.

Several new research questions have evolved because of the study's findings, offering a greater knowledge of the future direction of this research.

- How can sensor technology be tuned to detect obstacles and navigate terrain in extreme Arctic weather conditions, such as heavy snow and ice?
- What advances in machine learning algorithms are required to improve autonomous cars' decision-making ability in unexpected Arctic conditions?
- How can real-time meteorological data be integrated to improve the safety and efficiency of autonomous vehicle operations in the Arctic?
- What unique legislative and policy frameworks are required to facilitate the deployment and operation of autonomous cars in Arctic regions?
- How can public perception and acceptability of self-driving vehicles in Arctic communities be measured?
- What are the best methods for ensuring that autonomous cars' hardware and software systems work well in the severe Arctic climate?
- How can the existing infrastructure in Arctic regions be altered or enhanced to facilitate the widespread usage of self-driving vehicles?

Moving forward, this research will take a multifaceted approach. Collaboration among technology developers, politicians, and Arctic people is required to answer these research questions. Furthermore, pilot studies and field tests in Arctic settings will give essential data for improving technology and methods. Continued developments in AI and sensor technology, together with rigorous regulatory frameworks and community participation, will pave the road for the successful integration of autonomous cars in the Arctic, revolutionizing mobility and improving the quality of life.

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Declarations

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