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A Comparative Survey of LiDAR-SLAM and LiDAR based Sensor Technologies

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***Abstract*— Simultaneous Localization and Mapping (SLAM) accomplishes the goal of concurrent localization and map creation based on self-recognition. LiDAR-based SLAM technology has advanced exponentially as a result of the widespread use of LiDAR sensors in a variety of technological sectors. This paper begins with a brief comparison of the different sensor technologies such as Radar, Ultrawideband positioning, Wi-Fi with LiDAR, and its functional importance in automation, robotics, and other fields. Classification of LiDAR sensors is also briefly discussed in tabular form. Then, a LiDAR-based SLAM is introduced by discussing its general graphical and mathematical modeling. After it three main features of LiDAR SLAM i.e., mapping, localization, and navigation are discussed. Finally, the comparison of LiDAR SLAM is discussed with other SLAM technologies and the challenges faced during its implementation.**

Keywords—SLAM, LiDAR, Robotics, Robot Operating System, Deep learning, Human Computer Interaction.

I. INTRODUCTION

Position and localization are the two main features of Simultaneous Localization and Mapping (SLAM). This is a big open issue in mobile robotics. An autonomous robot has a complex problem, that is it needs to move precisely and draw an accurate map of the surrounding environments but the sensor in these robots needs to know exactly where they are to construct a specific map [1]. As a result, simultaneous map creation and localization are first-hand challenges. The Extended Kalman Filter-based SLAM (EKF-SLAM) was proposed in 1990 for calculating dorsal distributions over robot stance as well as benchmark positions [2]. In addition, the robot identifies its own location and orientation through repeated identification of spatial characteristics throughout the movement, and then produces a progressive map of the surrounding region based on its own position, achieving the objective of simultaneous positioning and map formation [3-7]. In recent years, localization has been a highly complex and contentious problem [8].

Localization technologies differ based on the environment and requirements for efficiency, accuracy, velocity, and reliability, which can be achieved by Global Positioning System (GPS) wireless signals, Inertial Measurement Unit (IMU), and among other things [9-11]. GPS can fail to operate for a variety of reasons, including power loss, inaccurate transmissions, intense environmental hazards such as heatwaves, and non-penetration through concrete walls or buildings [12]. A major drawback of routing for IMUs is that they usually have a cumulative malfunction [13]. As the control system continuously integrates acceleration in time to quantify speed and distance any calculation errors are accrued over time, however minor they may be [14]. One may think of the Global Navigation Satellite System (GNSS) as a resolve to this issue of localization, but it was soon found that GNSS alone was not enough. While the exact limitations of the classical GNSS solutions are removed, the existence of accurately located ground units continues to be a problem [15]. Satellite transmissions are being affected by the unpredictability of environmental phenomena. They can also disturb immediate signal reception and trigger multipath or non-line-of-sight damage, which may be disastrous for the area covered [16]. This form of transmission degradation is difficult to detect and usually results in a credibility deficiency that is difficult to resolve [17]. These problems are most common in densely populated urban areas with massive structures suspected of concealing satellites [18]. With the fast development SLAM equipped with a camera, IMU, LiDAR, and other sensors sprang up in recent years and these problems are being overcome gradually and consistently [19].

II. LIDAR SENSORS

LIDAR is an acronym for Light Detection and Ranging. It is a virtual perception device utilized to check the earth's exterior surface. It comes under the category of Time of Flight (ToF) sensor [20]. LiDAR measures the object distance by emitting laser to the object and capturing the travelling time [21]. A typical LiDAR sensor and its main elements are shown in Fig. 1.

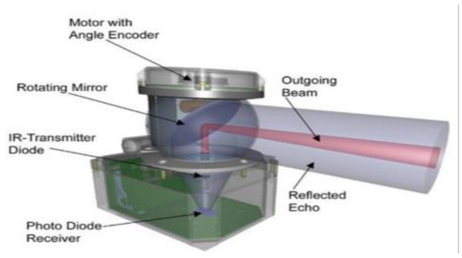

Fig. 1. Typical LIDAR Sensor and its main elements [22].

The precise formula for measuring the distance travelled by a returned light particle to and from an object is defined by

$$D = \frac{SL \times FT}{2} \quad (1)$$

Where, D is distance, SL is speed of light and FT is flight time. This helps in calculating precise distances to the land points, altitudes, as well as base ground buildings, roads, and trees [29]. The LiDAR equation (2) is used to quantify individual estimates on the atmosphere as well as assess the geometry and efficiency of structures [30] is as follows,

$$PR = S_p C_F \times GR \times PT^2 \times TB \quad (2)$$

Where, PR is power being received depending on range, $S_p C_F$ is continuous system-dependent consideration such as energy transmission and optics performance, GR geometry measurement as a distance function, PT^2 transmitting element of propagation channel and TB is backscattering attributes of the mark. These elements can be extended and modified to accommodate for the unique characteristics of each device and operation.

A. 2D vs. 3D LiDAR Sensors Technologies

2D LiDAR sensors record X and Y parameters using a single axis of beams [17]. 3D LiDAR sensors work in the same way as their 2D versions, but additional measurements around the Z-axis are needed to collect true 3D data. Data from the third axis is usually collected using several lasers at various angles or longitudinal projections. 3D LiDAR sensors have higher precision and resolution than 2D versions, but they are significantly more expensive. 3D LiDAR is ideal for visualization and thorough analysis of technological structures such as bend radius.

TABLE I. 2D VS 3D LIDAR SENSOR TECHNOLOGY

LiDAR Sensor Technology	Parameters			
	Wave length (nm)	Scanning Range (°)	Weight (kg)	Precision (mm)
2D	905	0°-180° 40°-140°	4.5	±15
3D	750	360°	05	±0.95

B. Mechanical VS Solid-state LiDAR

Mechanical LiDAR is difficult to incorporate on a small computer due to its large volume and mass. For example, keeping a mechanic LiDAR for building inspections [16] dramatically reduces the life cycles of surveillance drones. That's why a mechanical LiDAR cannot be built into a handheld device due to its massive size. The recent implementation of solid-state LiDAR provides a low-cost and compact option for LiDAR SLAM systems. A solid-state LiDAR is a structure that is entirely based on a microprocessor and has no mechanical components [19]. As a result, when opposed to mechanical LiDAR, both the size and mass can be greatly decreased. Furthermore, by replacing a rotating mechanical base, the LiDAR solid-state is vibration resistant. A mechanical LiDAR costs just 10% of the existing solid-state LiDAR, is as compact as a cellphone and has enormous potential for becoming a dominant small-sized sensing system, such as Augmented Reality [17], aerial exploration, and target detection. In terms of reliability, solid-state LiDAR is said to have a precision of 1-2 cm and a visible range of hundreds of meters. As, mechanical and solid-state LiDAR outputs are similar, LiDAR SLAM has not been challenged till now. Current techniques for mechanical LiDAR sensors have mainly been developed, which gather data from nearby objects by rotating a high-frequency laser device. Despite the fact that large-scale mapping studies have shown promising results [13][14], they are seldom used owing to their high expense.

C. LiDAR VS Other Localization And Positioning Systems

LiDAR is among the many popular perceptive mechanisms in robotics due to its extreme precision, wide-coverage, and long longevity. It measures target length and time travel by emitting lasers on the target. Techniques for localization frequently rely on external setup, resulting in a lack of durability in a range of circumstances. Ultrawideband positioning [13] needs multiple connectors to be preinstalled and optimized, while Wi-Fi [12] necessitates several routers, in general, to be extremely precise. Most active radars have a wavelength of 2–30 cm, while LiDAR's have an operating wavelength of 300–2000 nm [29]. This is a five-magnitude difference that can have serious implications for surveillance applications. Due to the closer spacing of laser beams, LiDAR's have smaller tracks and better angular and temporal resolutions than Radar. Low-wave radar is susceptible to water droplets and snow falling while LiDAR uses these aspects to detect and measure atmospheric molecular quantities such as oxygen and liquid water content [30].

D. Practical Importance of LiDAR Sensing Technologies

In terms of data recognition and application, LiDAR has advanced from a variety of other technologies and sensors that were not sensitive enough. LiDAR has proven to be a powerful tool for a variety of problems, including scanning between trees, by providing a smooth, precise, and direct 3D-mapping system that produces accurate and easy-to-understand results [3]. LiDAR technology is also acquiring prominence rapidly in robotics technologies where good validity and consistency are desired. These characteristics set LiDAR apart from other alternatives, such as photographic techniques, which had difficulty detecting ground elevations. Modern LiDAR's can also operate 24 hours a day giving them a significant edge against sensors such as cameras, which are almost useless in the darkness or mist [30]. The robust versatility of LiDAR, as well as its large range of up to 200 m and increased distance width, allows it to easily identify targets. Furthermore, the cost of such higher performance 3D sensors has been greatly reduced with the advent and adoption of solid-state technology, making it better suited for a multitude of applications.

E. LiDAR Pros and Cons

LiDAR sensors gather data from inaccessible areas easily and accurately[2-4]. They can be combined with other sensors such as IMUs, cameras, GPS, sonar, and ToF sensors [7-9]. Because of efficient lighting sensor technology, it can also be used in both daytime and darkness[11-15]. Once fully configured, a LiDAR is a self-contained piece of hardware that can operate on its own [22-30]. Depending on the development's specifications, LiDAR can be expensive [3]. This sensor technology is made inefficient in the rainy season and low-hanging weather [18]. Analyzing vast amounts of data can be time-consuming and resource intensive [20]. The strong laser beams used in certain LiDAR systems are harmful to the naked eye. It has a tough time penetrating dense material [32].

TABLE II. COMPARIOSN OF DIFFERENT TYPES OF LIDAR SENSORS

LiDAR Type	*Operation*	*Attribute's*	*Drawbacks*	*Applications*
Airborne [23]	The location and attitude of the sensing technology, as well as the laser scanner, are continuously measured.	Gives correct distance estimate and core land property information.	To travel long distances, very powerful transmitters are needed, making them a very complex and expensive technology.	Forests Topographic mapping. Ocean bed scanning.
Topographic [22]	Observing and modeling a region's topography	Used in the development of topographic maps.	When gathering data, impulses may not be able to pass dense foliage.	Silviculture, climatology, geochemistry, and environmental development.
Terrestrial [21]	Acquires the XYZ location of different positions on the ground by generating laser pulses against these positions and determine the distance between the system and the mark.	Retrieve sets of data with a maximum degree of accuracy and intensity.	They are unable to infiltrate buildings foliage and frost.	Earth tracking, shift tracking, reporting, simulation, and other landscape insights.
Static [19]	They are advanced devices that work similarly to high-speed complete channels.	It is a series of LiDAR laser scanning collected from a fixed spot.	The interval between the captured light and the referential causes the mixed beam to shift frequency constantly or break frequency in a static objective.	Logging, inspecting, archaeology, and engineering.
Solid-state [19]	These sensors are built on silicon chips that do not need manually rotating components.	It is a cutting-edge innovation that is better in performance, faster, quite space-saving, more robust, and less expensive.	It cannot spin 360 degrees and can only track objects in front of it.	Autonomous driving vehicles, automotive sector, and autonomous robots.
Mechanical [32]	Data is collected by manually spinning a beam/receiver unit, or by steering laser rays with a spinning lens.	They use strong collinear beams and highly targeted optics to concentrate the reflected signals on the detectors.	They are expensive, less technical, have performance problems and are wide in size.	Airborne laser swath mapping, geomatics and geomatics.

III. 2-D LIDAR SLAM

A 2D-LiDAR-SLAM architecture is equipped with a LiDAR sensor for creating a 2D map of its surrounding [5]. LiDAR sensor illuminates the target with an active laser "pulse," and calculates the distance from the object. LiDAR-based SLAM is a quick and precise solution for map generation of various circumstances and landscapes [17].

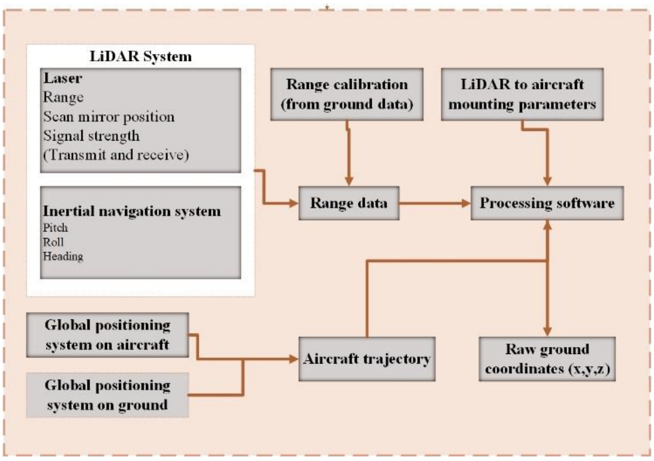

Fig. 2. General 2-D LiDAR based SLAM Graphical model.

A. Mathematical Modeling

A robot's agility and the availability of a system retrieving knowledge about the surroundings are the bare minimum requirements for solving the LiDAR SLAM problem. The general scheme of single-robot-based LiDAR SLAM can be interpreted from Fig. 2. The problem of LiDAR SLAM is described as: A robot wanders in an unfamiliar area and starts from a known location/points. Its motion is unpredictable, and determination of the next coordinates increasingly becomes more complex. The robot perceive its surroundings as it travels but it is quite difficult to create a map at the same time of deciding the robot's location. 2D LiDAR SLAM is a probabilistic term. The orientation of both the robot and the landmarks is measured at the same time, as seen in Fig. 3. The precise location of a robot and milestones is unknown and unmeasured. The conclusions are based on actual robots and prominent locations.

T: *Time*

r_t: *Location of the robot.*

R_t: *Succession of the robot position.*

o_t: *Change in position between $t-1$ and t.*

O_t: *Robot's relative motion.*

m_i: *Map consisting of milestones, locations and landmarks.*

M_t: *Succession of calculations between robot and locations .*

For robots, r_t is made up of its plane location (2-D array) and in-plane alignment (3-D array). The robot route R_t is represented as follows when time t = 0:

$$R_t = \{r_0, r_1, r_2, r_3, \dots, r_t\} \quad (3)$$

Relative motion O_t of the robot between time t-1 and t is:

$$O_t = \{u_0, u_1, u_2, u_3, \dots, u_t\} \quad (4)$$

It is not sufficient to depend solely on robot odometry. O_t to determine robot position inside a plane because it lacks the precision needed for precise localization in real-world applications. It is caused by the surface structure of the environment and robot misbehavior, such as wheel slippage. The continuous sensory estimation M_t with respect to time is described as follows:

$$M_t = \{m_0, m_1, m_2, m_3, \dots, m_t\} \quad (5)$$

Following the collection and specification of all relevant data, the next step is to forecast the landscape and location map. LiDAR SLAM approach makes use of a probability system that uses a probability density function to predict the robot and the location of the generated map. The probability distribution structure, P, is defined as follows:

$$P(r_t, m_i | O_t, M_t) \quad (6)$$

The relationship between the position of the robot $r_t$and change in position o_t which is defined as:

$$P(r_t | r_{t-1}, o_t) \quad (7)$$

Data collected from other landmarks and the previous robot position at time step t will be used to improve the robot's location and milestone measurement at time step t - 1. The process is repeated indefinitely to adjust the robot's measurements until the robot has finished exploring the field.

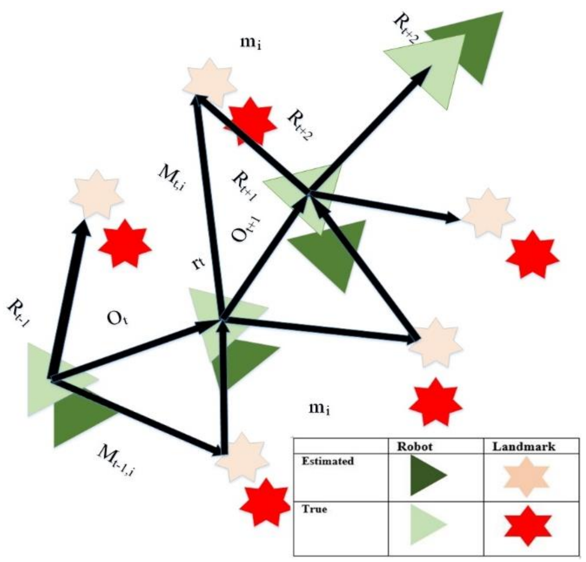

Fig. 3. Mathematical Modeling of 2-D LiDAR SLAM.

B. Features of 2D-LiDAR SLAM

LiDAR SLAM is equipped with three main characteristics, map of surrounding areas, localization and path planning.

(a) Mapping: It contains a map of the surrounding area that the robot wishes to visit before beginning to navigate across new areas. Mapping allows autonomous robots to build an atmosphere map using the hardware sensor for receiving environmental data [5]. For map representation forms, data generate a diagram that is a mixed or a topological map [3].

(b) Localization: One of the SLAM capabilities is identified as a robotic system that can measure and predict the milestone location and direction, based on the mapping [3]. Localization allows wireless entities to "think," find points of reference and identify narrow barriers with map-info [2] by calculating and evaluating the route. The positioning allows the robot to acknowledge its position and surroundings and to stop when an object is in sight.

(c) Navigation: These capabilities combine navigation and positioning features, where the robot has a reasonable direction schedule for the data collected during detection and localization. The visualization and position protocol were done recursively to adjust the robot's knowledge about its surroundings as it navigates its surroundings [2]. Navigation chooses a suitable path dependent on the details obtained, responds to the local area, and can return to the beginning or stopping points after exploring.

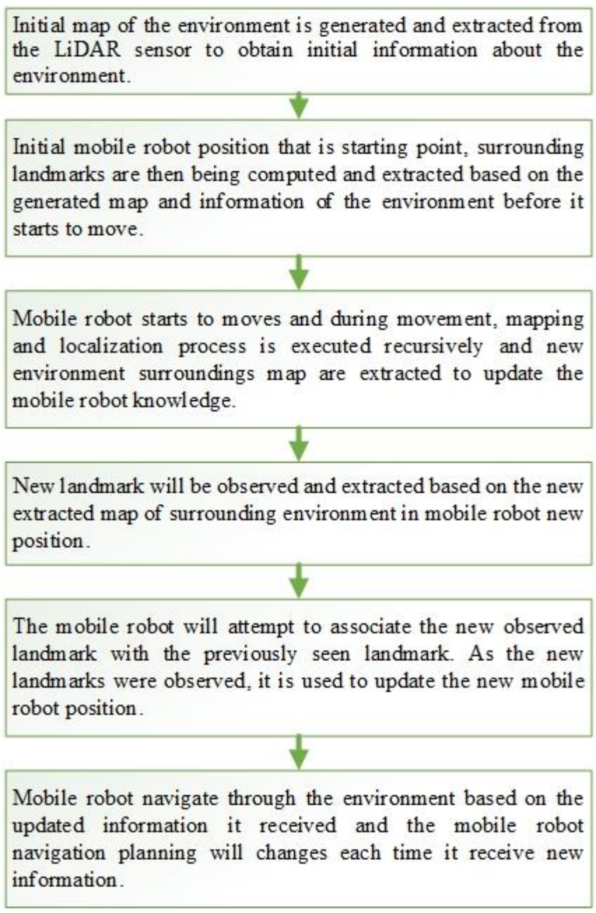

Fig. 4. Overview of 2D-LIDAR SLAM.

C. LiDAR SLAM VS other SLAM technologies

Table III shows the comparison of LiDAR SLAM with other SLAM technologies in terms of operation advantages and disadvantages.

TABLE III. COMPARIOSN OF DIFFERENT TYPES OF SLAM TECHNOLOGIES

Sr No	*SLAM Type*	*Operation*	*Advantages*	*Disadvantages*
1.	**2D-LiDAR SLAM [5]**	Using a laser sensor, this algorithm creates a 2D view of its surroundings. It calculates the distance from an object by lighting it with an active laser "pulse."	Best to spot unfunctional structures like hollow ceilings. Has maximum performance, good precision, significant distance range.	2D-LiDAR based methods fail in bad weather like thunder.
2.	**EFK (Extended Kalman Filter) SLAM [15]**	EKF-SLAM derives the device status value estimation by triple phase iterations i.e., prediction, observation and update. [15]. It can be regarded as a Bayesian filter variant.	Recurrent or more accurate estimates of the condition of a complex framework. Tackles unsuspected, combinatorial assessment challenges until a strong screening challenge is screened.	Sophisticated probability statistical calculation. Forecasting is not dependent on facts.
3.	**FAST-SLAM [14]**	Resolves the dilemma of data correlation with the highest estimate of probability [14].	M · K tiny EKFs (K of them in each particle).	Absolute probability statistical calculation. Estimation focused on non-reality
4.	**LSD (Large-Scale Direct) SLAM [13]**	Specific vision - based methodology: a pixel-specific stero-sphere correlation provides effective photo orientation via webcam and geometry through semi-densely deep masks [13].	The picture intensity works directly rather than the major step process. Greater precision, further strength in a sporadically patterned setting, Follow Sim (3)-constraints (e.g., solid body movement scale) within the current frame specifically [13].	Costly. Less precise.
5.	**GRAPH-SLAM [12]**	The technique utilizes a stochastic gradient descent analogous to an adaptive procedure for non-linear optimization. With regard to the posterior robot path, each restraint gives a circle.	Rapid without including estimated density factoring [3].	The limitations in the stance diagram are taken one by one time. Knowledge ambiguity, disturbance data.
6.	**PF (Particle Filter) SLAM [11]**	A Particle filter is a Monte Carlo sequence filtering system, with particle filters or other filters being obtained via the PF-SLAM [11].	The filtration is carried out with state identification, mass modification and resampling [11].	Many particles in high spatial domain are likelihood to be spaced and faraway.
7.	**Visual-SLAM [10]**	Uses the whole picture by removing aspects to identify and map most prominent and essential positions.	SWAP-C Low (Low Size, Weight, Power, and Cost). Semi-dense graph, no identification function necessary. Quite thick, identification of specific range, sample rate "Infinite."	Because of their illumination adjustments vulnerability and low texture climate, it is sensitive to flaws. Costly sensors only detect environmental changes.
8.	**ORB (Oriented FAST and Rotated BRIEF) SLAM 2 [9]**	It is more feature based and uses ORB features because of the speed in which these can be extracted from images and their rotational invariance [9].	High speed extraction processes.	High computational cost due to high pixels cameras, mathematical computation complexity.
9.	**Open Rat SLAM [8]**	It designs the mechanism of steering on the hippocampus (a part of the mammalian brain) [8].	With only a few modification parameters, the Expression Navigation System evolved a variety of cognitive models for navigational elements and topological maps across these dramatically different datasets [8].	Needs high pixels cameras. High computational cost.

LiDAR-based SLAM offers a device-free environment for robot navigation both indoors and outdoors [3–5]. Furthermore, unlike other SLAM systems like ORB-SLAM [9] and Graph-SLAM [12], 2D-LiDAR SLAM [5][17] is unaffected by disruptions like temperature/light changes. It has been commonly used in a wide range of autonomous applications, including autonomous driving [10], building inspections [11], and smart fabrication [12].

IV. Challenges

In SLAM, volatility, interaction, data combinations, and time variability arise from many main problems. Here we addressed each issue is to see its effects on the LiDAR SLAM.

A. *Uncertainty*

Two main problems, called position and hardware instability, rises due to uncertainty [16]. Both problems have enormous effects on LiDAR SLAM's results. The complexity of position is one of SLAM's challenges in determining how the mobile robot can navigate the many paths in the environment. The robot can travel easily from one point to another in a single linear direction, as it can be tracked to the original point [15]. In actual environments, however, the mobile robot can crawl and maneuver from one point to the next in several ways. This dilemma is also highly disruptive. Thus, this dilemma makes the mobile robot take the right direction so that it can know its current or absolute status as it is highly unsure about its position. The generation of chipset noise in different parts of autonomous robots led to derived information being inaccurate [32] in the case of hardware instability. This incorrect information is therefore measured analyzed and subtracted to identify the real/absolute location, reference, and other related information of the robot.

B. *Correspondence*

Interaction is known as the toughest challenge in LiDAR-SLAM and these issues have a major effect on the SLAM method of identifying landmarks. This is because SLAM is distinctive and differs from other known landmarks [17] in its capacity to identify one specific landmark. Two various hurdles such as two rocks, rock A and rock B, are used as a basic example. The one thing that differs is that rock A is somewhat larger than rock B. Both rocks have identical forms. The distinction is recognizable by humans, but not by robots. As humans know, the capability of a robotic system to distinguish landmark identifiers is not easy, so it depends on the hardware to display or quantify the environment [15]. Since the knowledge from autonomous vehicle hardware such as a laser sensor is retrieved, the new landmark cannot be recognized by the robotic manipulator, if it still differs or is equal to the previously identified landmarks.

C. *Data Association*

In the context of problems with data association, it affects the LiDAR SLAM capacities to allow the robot to revert to its original or previously mapped area [16]. This problem was noted when the autonomous robot tried to link the current location with the previously identified landmark to return to the previous source or mapped region. To approximate the main relationship of robotic manipulators, data analysis was used to return to the robot’s origin based on a prior map and known points of reference [17].

D. *Time Complexity*

Problems regarding time complexity tells us the difficulty of how quickly the LiDAR SLAM can perform calculation or do processing and compute the gathered data points which produces the intended effects that the autonomous robot will use in future [31]. As we know, during orientation LiDAR SLAM simultaneously and iteratively performs mappings and location processes. These multiple simultaneous systems need to be coordinated and configured properly in a limited period. The efficiency and timescales in the SLAM methodology or methods then become the main element to provide the robotic system with accurate results to experience new things effectively and decrease error rates [32].

E. *Physical Devices*

LiDAR is influenced by physical technology. The spatial accuracy in the longitudinal plane is low in comparison to the diagonal tilt [23-27]. The sweeping theorem also affects it. As one step farther from the LiDAR center, the point cloud shrinks in size, and when the limit is reached, the LiDAR stops receiving datapoints [28]. The above three points spread the LiDAR point cloud on the scanner scale [29].

Thus, LiDAR-based SLAM technology must solve issues such as massive computing, scattered coordinate system, and movement manipulation.

Conclusion And Future Work

Several engineering experiments have been conducted to determine the best method for producing a functional autonomous system. The majority of research relies on simulation or location as a differentiation process. However, as time passed, a new concept known as LiDAR SLAM was added. LiDAR SLAM demonstrates the ability of autonomous mobile robots to execute navigation and position operations at the same time. It increases robot efficiency while managing a dynamic environment without human intervention. LiDAR SLAM has been a tremendous advance in the resolution of the portable automated robotics quandary, and it is also regarded as an aspiration in the world of autonomous robots. Its effectiveness in resolving the mobile robot mapping and position problem leads significantly to the self-exploration of robots. In a nutshell, LiDAR SLAM is a convincing solution, but it remains to be seen how far this evolved algorithm can effectively accomplish the ultimate goal of SLAM innovation in the automation of the robotic system. Many questions exist about the core aspects of the 2D LiDAR-SLAM and its implementation. As a result, a thorough understanding of LiDAR-SLAM and its use in mobile robots for artificial intelligence is needed. With recent advancements in LiDAR-SLAM growth, it can be easily extended in a variety of fields, with positive outcomes in the future. We are proposing to integrate the software in the LiDAR SLAM as future work. Soft computing is a tool utilized to solve computational challenges that are complicated and arithmetically persistent[18]. It provides a flexible and effective distribution mechanism for SLAM problem-solving. The principal goal of this concept is to boost and maximize the robot accuracy, measurement and reduce failure frequency to increase the efficiency of LiDAR SLAM. The idea is not novel, and many works have already been completed; this concept has been proposed as in [19-20]. The suggested hybrid approach incorporates the FastSLAM algorithm with genetic [19], specifically swarm optimization soft computing methodologies [20].

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