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A Review on Localization Algorithms of Mobile Robot in Different Environments

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***Abstract*: -** The mobile robots' localization algorithms are considered the main part of robots to make them self-driven. However, most of the localization algorithms have a common problem related to the noisy reading of the sensors during Simultaneous Localization and Mapping (SLAM) of the environments. The noise produces errors in the estimated path which will lead to wrong decisions when handling the localization process. Thus, there is a need for an algorithm to eliminate the noise and correctly estimate the robot's position along with the movement. This paper classifies localization algorithms into three groups, namely, Kalman Filter based approaches, Statistical based approaches, and Artificial intelligence-based approaches. The reviewed algorithms have been arranged from the oldest to the newest with their results, researchers' methods to treat the noises, and tools for sensing the environment (camera, IMU, LiDAR, LRF, and Ultrasonic). One can notice that Kalman Filter-based approaches were used rarely in the previous years, while the statistical-based approaches were

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combined with other calculations to enhance their performance. The modern approaches used nowadays are AI-based approaches, especially fuzzy logic algorithms. The results of the reviewed algorithms proved that the noises are still affecting the algorithm's performance even though one can use modern algorithms to eliminate all the noisy readings. The laser simulator logic algorithm that has been used in the Active Force Control (AFC) of mobile robots gave the best results in eliminating the noises. This work reviews most localization algorithms and classifies them based on how they are used for pose estimation; it can be a useful reference for researchers who will work in this field in the future.
Key-Words: -Localization algorithms, SLAM, Mobile Robot, Simultaneous Localization and Mapping algorithms, Localizations' sensors, Autonomous Robot Systems

1 Introduction:

Mobile robots have become attractive and an exciting research area since the end of the past century due to their main use in the manufacturing field and military experiments for a long time. The main reason for this importance is to make the robots able to do things that are dangerous to humans, or things that humans cannot do at all, such as explosive detection and carrying out the danger assessment instead of people doing them. The other use of the robot is in the medical field, especially in modern medicine for the monitoring of the spreading of viruses and infections that threaten human lives. A recent example is a COVID-19 pandemic and the associated restrictions; all these things make the robot helpful for human life. Nowadays, advanced mobile robots are becoming self-driving (autonomous) regardless of how they are moved (humanized, wheeled, or aerial). For robot automation, it must know the environment, understand the map of the environment, and locate its position on the map to make the correct decision on where to go in the next move[1]. To make robots do this complex step, algorithms were provided by researchers to achieve the process of localization and mapping. Autonomous mobile robots also depend on other approaches to move in the environment, such as Path Planning and Trajectory algorithms. However, these approaches also need the SLAM to understand the surrounding environment; therefore, localization algorithms are the main parts of the autonomous robot's systems.

SLAM stands for simultaneous localization and mapping, where two or more processes are done simultaneously. The localization means that position is estimated along with the robot's movement through sensors and an environment map. The localization and mapping must be done at the same time. The term SLAM contains two steps; the first step (localization) is done using sensing tools such as (camera, LiDAR, Laser Range Finder, and IMU). After that, the data are collected from sensors, then combined in the robot system, then the algorithm processes the data to estimate the location to make the right decision.

The second step is map building and locating the robot's current pose on the drawn map. The mapping process collects the data from the sensors or visual sensor (camera) to select some of the known locations used as anchors in the mapping process and locate the robot pose on the map. Fig 1 shows the General Localization and Mapping process. The anchors in the mapping process are called landmarks (such as walls, tables, or signs). The localization and mapping are done according to the sensors' data, such as range, bear, or other data. The data can be used in triangulation or other methods to estimate the robot's pose and its pose on the map. SLAM algorithms have solved the problem of localization and mapping, but they are still not accurate [2].

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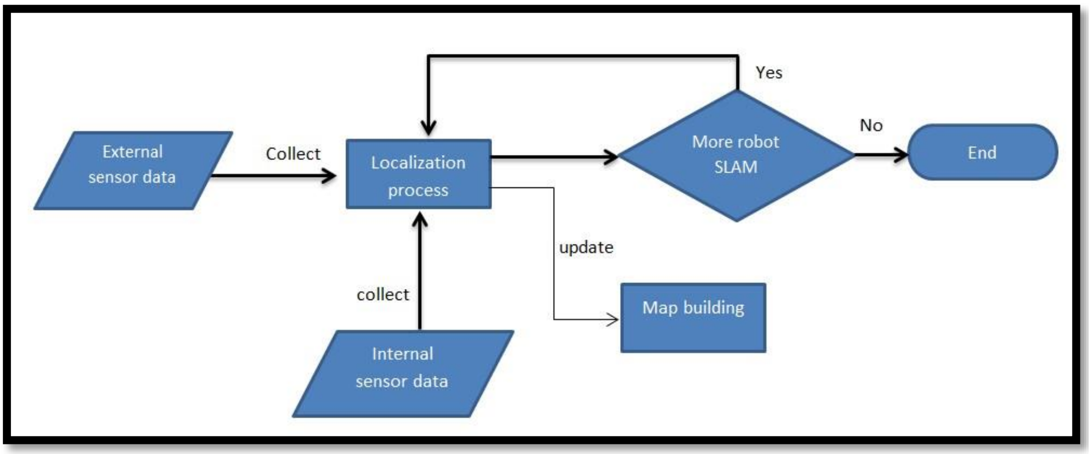

Fig 1. show the general localization and mapping

For this reason, many algorithms have been provided, each with its limitations (advantages and drawbacks). Algorithms are also different in the calculations and sensing tools that algorithms work with. Some of the approaches are powerful in a static environment, and others work in the dynamic environment. There are other properties, such as working in an indoor or outdoor environment. Some algorithms employ the visual aspect in the localization process, typically done by a camera (mono or stereo), so-called VSLAM [3]. Combining the visual aspect and the sensors makes the algorithms more efficient. The other aspect is adding the Inertial Measurements Unit (IMU), also known as Inertial Odometry. The IMU and the visual aspect can give good results [4]. This work will address algorithms that often work with wheeled mobile robots.
Some of the previous works face the problem of noise coming from the sensor's readings. The noisy readings lead to minor errors, but these small errors get propagated due to the cumulating errors. The error becomes significant enough, causing the robot to make wrong decisions for its next step [5]. Some algorithms or methods are applied to do the process of error rejection, such as the probabilistic methods (Bayesian and others) [6].

2 Sensor and Noise

The common sensors used for localization are LRF, camera, RFID, and Odometry. LiDAR and OptiTrack Cameras are used for localizing the robot in a roundabout environment [7]. Camera and LiDAR with IMU sensors are also used for pose estimation in a 3D environment [8]. IMU, wheel speed, and gyroscope sensors with the help of Kalman Filter as a localization algorithm are used to build a pose estimation system [9]. Visual sensor (camera) and the Inertial Odometry (IMU) can be combined to achieve accurate localization by Range Focused Fusion algorithm [10]. Most robotic projects use sensors for the localization and mapping of mobile robots. UAVs (Unmanned Aerial vehicles) also use the same sensors with the addition of an Ultra Wide Band sensor or Satellite image as proposed in the work by [11].
Moreover, Under Water robots use the pre-mentioned sensors (Inertial Odometry) and some other sensors (infrared, sonar, and ultrasonic) for localization and mapping [12]. SLAM algorithms can employ only one of the standard sensors to perform the localization, but the results will not be perfect.

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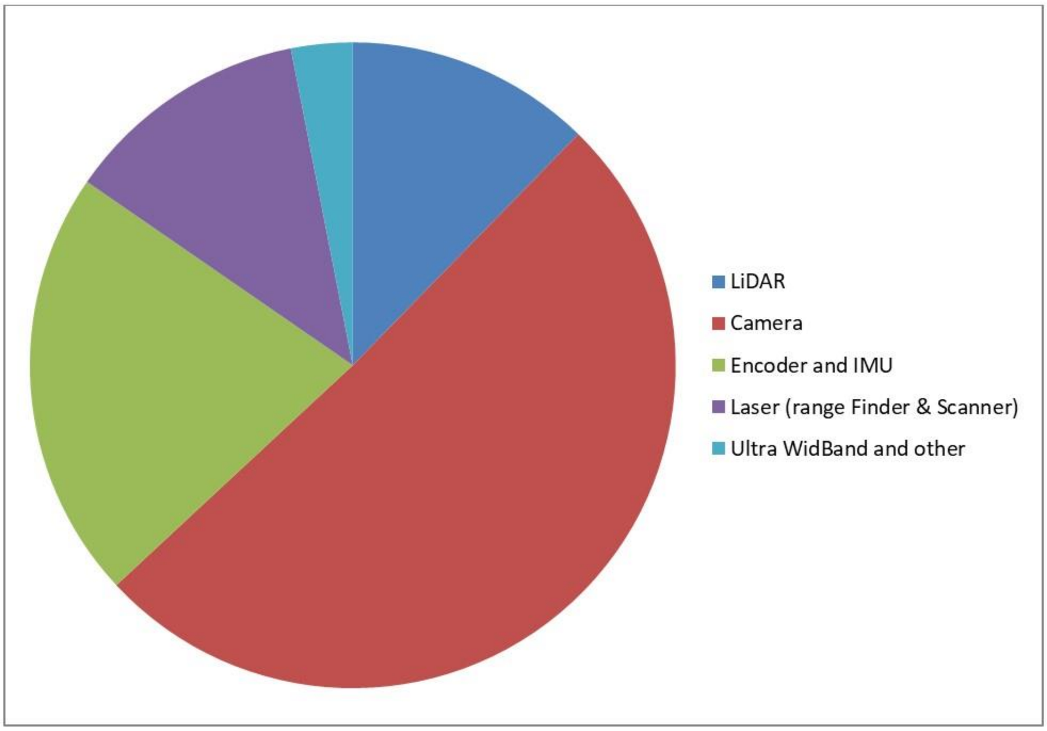
For example, the authors in [13] used only a stereo camera as a sensing tool but did not achieve good results.

On the other hand, in [14], the authors used LiDAR and Inertial Navigation System, while the authors in [15] used a camera and ultrasonic sensor to achieve good results. The type of environment



sometimes affects the sensor to be used; for instance, in a glass-walled environment, the camera will not be as accurate as Laser Range Finders [16, 17]. Figure 2 shows the sensors used in the reviewed works.

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Fig 2. Show the sensors used in the reviewed works

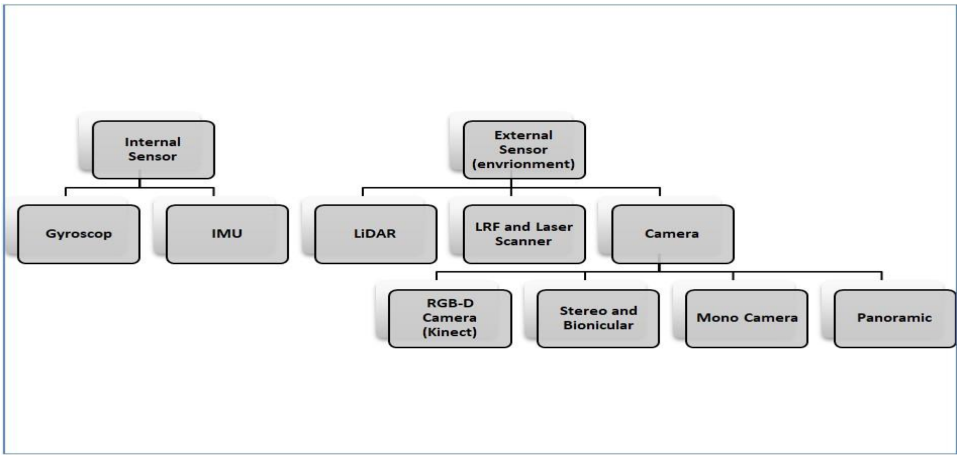

Figure (3) taxonomy of sensors used the localization process

3 SLAM Algorithms

SLAM algorithms vary in their working method, and there are many classifications for these algorithms. Some use the Kalman filter as a base for their work, while others use Artificial intelligence algorithms to do the computational process; some other algorithms use Statistical computations for localization. This paper classifies SLAM algorithms into three main categories: Kalman Filter-based, AI-based, and statistical-based algorithms. The listing of the previous work will be based on a date, from relatively not old (2015) to the recently published.

3.1 Kalman filter-based approaches

The computations time and memory consumption are significant in the localization process. Bresson et al. [18] proposed an algorithm based on Kalman Filter named MSLAM which is a linearization-free algorithm and produces 3D uncertainties in images. The results show that the algorithm achieves accurate localization, but there is a problem with losing the landmarks when the illumination is changed.

The 6DoF (degree of freedom) visual SLAM with Extended Kalman Filter (EKF) was proposed by [19], and named StrcutSLAM. The algorithm depends on the building's structure lines to cope with the lack of point features in the environment. The results show good positioning and orientation in the localization process. As a weakness, the algorithm also treats some buildings' structure lines as outliers and the duplication of lines caused by the threshold value.

Robotica (robot factory) is an example of mobile robots' industrial application. The factory depends on robots to do some tasks, but the robots face a problem with the dynamic environment and the obstacles that may intercept the robot path. The authors in [20] used an algorithm named Perfect Match (PM) with the help of the Extended Kalman Filter (EKF) to solve the problem of path interception. The proposed method reduced the error between the measured and expected distances, and the experiments show promising results in localization and path drawing.

The static environment in the real world is not as it is assumed to be as there is always a dynamic scene. Therefore, Evers & Naylor [21] proposed an algorithm called Generalized Motion SLAM

(GEM-SLAM) which is based on a probability density filter that makes use of (EKF) equations. The performance of GEM-SLAM was better than that of the SC-PHD filter, RB-PHD filter, and FastSLAM..

The heavy computations in FastSLAM algorithms increase the difficulty in the estimation accuracy of SLAM. Luo & Qin combined two algorithms - Box-PF (Statistical-based) and extended interval Kalman filter (EIKF) (Kalman filter-based), to solve the accuracy estimation problem [22]. The results show that the method can reduce the computational requirements and eliminate noise compared to FastSLAM.

Extended Kalman Filter is one of the earliest SLAM algorithms; however, with the development of new SLAM algorithms, it still has issues with the noises. An improvement for (EKF) (Kalman Filter based) based on Fuzzy logic and laser matching to enhance the pose prediction was proposed by [23]. The results show an improvement in the accuracy of the proposed method compared to the standard EKF. However, the method needs to be compared with other new algorithms.

Obstacles avoidance during the navigation of mobile robots depends on the accuracy of the SLAM algorithm used. Active SLAM is used with graph topology to enhance obstacle avoidance [24]. As a result, a collision-free trajectory can achieve good performance but the real-time experiment needs to be enhanced.

The changes in the environment affect the robot's path; this can help detect older people's activity. Authors in [25] proposed a method for taking care of older people by robots. The method used the EKF and wall-following algorithm with IoT to monitor the older people in real-time. According to the results, the robot works well for older adults with a good map and the best route selection.

External sensors are susceptible to noise from the surrounding environment, such as LiDAR, which is affected by light and dynamic objects. Graph-based Unscented Kalman Filter algorithm in [26] used IMU, RGBD camera, and LiDAR to reduce the noise. The experimental results show that the proposed method is more efficient than the Cartographer algorithm. However, the proposed algorithm needs more comparisons with other algorithms.

Robot systems can work independently with their platforms by embedding the localization algorithm in the system. The goal will be to reduce the computation complexity to put the SLAM algorithm in the robot system. Authors in [27] implemented the MonoSLAM E.K.F. algorithm in the robot platform using OpenCL. The algorithms are executed entirely on the robot and without any computer help.

Combining modern technologies with a relatively old algorithm enhances the algorithm's work. For example, the Hololens (augmented reality device) is combined with EKF SLAM algorithms by the authors [28] to minimize the error of the EKF algorithm. The results show that the new method reduced the calculations and constructed good maps. The future of this work is to use IoT infrastructure for energy reduction..

There are issues with localization using RFID and one of them is that UHF RFID does not allow the range estimation between reader and tag. The authors in [29] proposed a UHF RFID method with Multi-hypotheses Kalman Filter (MHKF) to solve the problem mentioned above. The efficiency of the method was proved in the experiment, and it can be applied in path planning and localization but should be tested first for complex environment localization

In real-time localization, the feature points extracted may arrive late at the robot processor, and new features are extracted; as a result, the robot location will be different from the late extracted features. The authors in [30] proposed an Extended Kalman Filter method that uses every single laser scan to

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make matrices of EKF smaller. Experiments in complex environments show good results and reduced computations. For a more accurate SLAM, IMU should be added to the method.
Path planning of industrial mobile robots is based on accurate SLAM. Authors in [7] proposed a method to improve the Extended Kalman Filter, and this is done by performing the linearization on the last estimation instead of intermediate estimation. The results demonstrate the robustness of the proposed method, and a suggestion to perform the method on different types of robots.
Landmarks observation is important to any SLAM algorithm because it helps pose estimation. From a geometric sight, the authors in [31] proposed a method based on the SLAM State-Space principle to get a bundle of landmarks. The results show decreasing cost of computations and memory requirements much lower than the EKF SLAM algorithm. Table 1 compares the above-mentioned Kalman filter algorithms' main features

Table 1 comparison between Kalman based localization algorithms

id	Author name	Algorithm	Environment type	Accuracy	CPU time or (speed)	Work type
1	[18]	MSLAM	Outdoor - large scale	~3.5(m) deviation in 200(m) trajectory	No	Simulation and Real-experiment
2	[19]	StrcutSLAM	Indoor - large-Scale	0.797(m) error for distance 0.012(rad) for Yaw (774 m)	No	Simulation and Real-experiment
3	[20]	Extended Kalman Filter (EKF)	Indoor - dynamic industrial environment	~3 (cm) in 288 (cm) trajectory	From 30 (ms) To 1 (ms) decreases during runs	Simulation and Real-experiment
4	[22]	extended interval Kalman filter (EIKF)	Indoor	For noise level (0.6m,4º) RMSE was 0.3m	0.573(s) & number of particles is 100	Simulation and Real-experiment
5	[21]	GEM-SLAM	Dynamic (or unknown)	Localization 96.54%, feature map 96.54%	No	Simulation
6	[23]	Extended Kalman Filter	Underground Mine environment	accuracy of y-direction 53.8% φ-direction 60.9% compared with the standard EKF	No	Simulation
7	[24]	Active SLAM	unknown environment and indoor environment	~ 0.2(m) in 5x5 (m) indoor trajectory	0.7 (s)	Simulation and real-experiment

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8	[25]	EKF (with wall following algorithm)	indoor environment	~ 30 (cm) maximum far from corner of the walls	10 (s) for 43 (cm) trajectory	Simulation and real-experiment
9	[26]	Unscented Kalman Filter	Indoor - large-Scale	0.2 (m) error in 8x10 (m) trajectory	No	Simulation and real-experiment
10	[27]	MonoSLAM E.K.F.	unknown environment	The mean error of trajectory 0.31 (cm)	Average processing time 17.5 (ms) per frame.	Implementation on OpenCL
11	[29]	Multi-hypotheses Kalman Filter (MHKF)	unknown environment	When the noise is 0.01 cm, the positing error is 1(cm) of 40 (cm)		Simulation
12	[30]	Extended Kalman Filter	unstructured outdoor environment	0.24–0.42% of position error and 0.078–0.141 deg/m of orientation error in localization	approximately 0.1 m/s.	Simulation and real-experiment
13	[7]	Extended Kalman Filter	unstructured environment.	~0.3 rad (for rotation) and 0.1 for the path	Robot speed 1 (m/s)	Simulation and real-experiment
14	[31]	SLAM State-Space principle	Dynamic environment	~0.3 m error in trajectory 5x5 m		Simulation

3.2 Statistical-based approaches

Dual-sensor-based Victor SLAM (DV-SLAM) algorithm was proposed to solve the problem of the measurements that come from fixed heading which will be ambiguous in the SLAM process [32]. The algorithm adopts RBPF (Rao-Blackwellized Particle Filter) and measures the vector field signals by two sensors in a specific location on the robot. Experimental results show improved accuracy of SLAM and increased loop closing ability (indoor). The algorithms still have disadvantages for the outdoor environment due to the reliance on the Earth's magnetic field sensors.
Khan et al. [33] provided an approach to make use of the laser's intensities data in the SLAM algorithms. HectorSLAM algorithm and laser intensities data can recognize the material surfaces by the reflection of the laser on the material surfaces. Moreover, the author uses this approach in pose estimation (near a wall, near a door). The method achieved accurate localization and acquired an excellent geometrical model in the indoor environment. Luminanceance will limit the laser reflection to the objects in open places for use in outdoor environments.
GraphSLAM based on LiDAR was used to minimize the significant errors that come from the noisy measurements 2D axis mapping [34]. The results of the 2D Map Axis were accurate in mining drift and indoor environments, but the algorithm needs more tests in an outdoor environment..
Buildings nowadays are not only made up of concrete or wood as glass panels have become the modern interface of new world buildings. The glass reduces the rangefinder localization's accuracy; Hence, Wang et al.[17] proposed the use of the GMapping SLAM algorithm to exploit the light reflection on the glasses to complete the localization process. About 95% of glass panels have been detected by the method in experiments in real-time, but not all types can be detected, such as mirrors.

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SLAM algorithms based on particle filter (PF) are ubiquitous, but there is a problem in particle degeneracy, like Box-PF. To enhance the algorithm and reduce the computational load, the authors in [5] proposed an algorithm that uses Ball-PF instead of Box-PF. The comparison between the proposed method, Box-PF, and RBPF shows that Ball-PF is more accurate than the others. For better results, the probability density functions must be selected by the author for the Ball-PF SLAM algorithm which is a statistical-based method.

Multi-moving objects (dynamic environment) form a problem for SLAM algorithms. A method for multi-target tracing coupled with the SLAM algorithm was proposed by [35]. The system detects and traces moving objects (DATMO) with RANSAC (SLAM algorithm). The method's effectiveness in a challenging environment was confirmed in the experiments.

Embedding SLAM algorithms in the mobile robot may be affected by large and complex computations. To increase the speed of the SLAM process, Yan et al. [36] proposed PF-SLAM which combines two SLAM methods, Particle Filter and FastSLAM. The proposed method increased the response time, and obstacles were quickly avoided in the dynamic environment during the robot navigation. The researchers compared FastSLAM to some of the previous works and found that this algorithm can be improved for better performance.

The authors in[37] proposed a method to enhance the FastSLAM algorithm which involves resampling. A square root filter was added to the improved FastSLAM (Statistical based). A comparison of the new approach to two editions of FastSLAM (SRUFastSLAM and STSRCDFastSLAM) showed that IFastSLAM achieved better accuracy than the others, but it needs to be optimized for real-time application.

Demim et al.[38] proposed an algorithm for localization to make the Unmanned Ground Vehicle (UGV) perform localization accurately. The proposed method, Adaptive Smooth Variable Structure Filter (ASVSF), is an extended form of the SVSF algorithm to improve the algorithm's performance. The results proved the enhancement of the performance and the computation time compared to the standard SVSF.

Sonar transmitters can be used instead of range finders for position estimation in a mobile robot. Normal Distribution Transformation (NDT) algorithm with a sonar sensor has been proposed by [39] for indoor navigation. The results of the experiments proved the efficiency of the proposed method for indoor environment localization.

Particles are used to describe robot state at a time instead of parametric values. These particles are used in the FastSLAM algorithm and degrade in the process of SLAM. Improving FastSLAM through variance reduction will increase the number of effective particles [40]. Experimental results demonstrate the efficiency of growing particles by this method, which leads to accurate SLAM.

Objects and robot locations are necessary to navigate a specific task using the map. Omni-directional means receiving signals from all directions and the tool for doing this is LiDAR. The authors in [41] proposed a method for SLAM using HectorSLAM (Statistical based) algorithm that relies on scan matching of LiDAR data. The algorithm achieved automatic navigation and map building in the experiments. However, the map should be 3D to realize Omni-directionality.

SLAM algorithms based on Particle Filters suffer from the degradation of particles, affecting pose estimation. A novel Opposition High Dimensional Algorithm (OHDA) for particle filter improvement was proposed by [42]. The method can complete pose estimation and map building. Experiments show that the proposed method performed better than the other recently proposed algorithm with lower error values.

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Giannelos et al.[43] revisited the use of a Particle Filter with an RFID localization system and proposed a new method to improve the (PF) approach. The proposed method is Robust-Distance Particle Filtering (RDPF) with RFID in which a weight metric was introduced for particles and measurements. The new method achieved high performance even with multipath and 3D localization.
The problems of the current SLAM algorithms are two factors, measurements of occupancy grid-map and the estimation of position online. The author in [44]. proposed B-Spline SLAM to address these problems. Basis-Spline is a spline function with minimal support respecting a given smoothness, degree, and domain partition. Evaluations show that the proposed method constructs an accurate map without floating-point measurements.
Table 2 summarizes the comparison between the main localization features of the above-mentioned statistical algorithms.

Table 2 comparison between statistical-based localization

Id	Author name	Algorithm	Environment type	Accuracy (Error)	CPU time or (speed)	Type of work
1	[32]	DV-SLAM	Indoor environment	Path error ~0.25(m) in 5x6 trajectory	N/A	Simulation and real-experiment
2	[33]	HectorSLAM	Indoor environment	Error in the path ~0.3 (m) in 5x5 trajectory	N/A	Experiment
3	[34]	GraphSLAM	indoor, outdoor, and underground environments	Error ~1(m) in Beamish-Munro Hall 40x30 (m) And ~10(m) in 1.3(km) path	N/A	Simulation and real-experiment
4	[17]	GMapping	Indoor environment (glass detection)	Glass detection ~95%. And the error is 0.5 (m)	N/A	Experiment
5	[5]	(Ball-PF) SLAM	Indoor environment	Error about ~4(m) in 200x250 (m) trajectory	For (50) particles 98.20 (s) as average	Simulation and real-experiment
6	[35]	(DATMO) with RANSAC	dynamic environment	Error in the path ~1(m) in 50x50 (m) trajectory	150 cm/s. the speed of robot travel	Simulation and real-experiment
7	[36]	Particle Filter& FastSLAM	dynamic environment	Error ratio about ~0.05% on the path	N/A	Simulation and real-experiment

8	[37]	IFastSLAM	Under-water large-scale environment	~0.4 (m) error in 20x20 trajectory	The number of particles 30 and (RMSE) is 0.4(m). CPU time is 83 (s)	Simulation and real-experiment
9	[38]	Adaptive Smooth Variable Structure Filter	dynamic environment	Error ~0.7(m) in 6x5 trajectory	N/A	Simulation and real-experiment
10	[39]	Normal Distribution Transformation	Indoor - large-Scale	~0.19 (m) error in 2x2 (m) trajectory	N/A	Simulation and real-experiment
11	[40]	improve FastSLAM	unknown underwater environment	Error about ~ 5(m) in 200 (m) trajectory	100 particles	Simulation and real-experiment
12	Rivai et al. [41]	HectorSLAM	Unknown indoor-environment	Localization Average error is 1.1%. mapping average error is 5.32%	N/A	real-experiment
13	[42]	Opposition High Dimensional Algorithm	5 simulated environments	~2(m) in 80x90 (m) simulated environment	100 particles 431(s) and error about 0.73	Simulation and real-experiment
14	[43]	Robust-Distance Particle Filtering	indoor environment.	~5% error in the trajectory	N/A	real-experiment

3.3 Artificial intelligence-based approaches

The authors in[45] had explained the sensors embedded in SLAM systems due to their importance, especially the Fuzzy logic-based SLAM. Scholars have shown that RGB-D cameras are preferred in building 3D maps with the depth channel, which is helpful to estimate distance.

The navigation of mobile robots consists of two processes, SLAM and Path Planning, to travel from point to point. Jajulwar et al.[46] proposed a method for SLAM and obstacle avoiding controllers based on Fuzzy logic. The method selects the shortest path to reach the destination. Experiments and simulations show that the proposed method performed as expected.

Landmarks are essential when using camera vision to make triangular localization. To make global localization with an accumulative error from noisy measurements, the authors in [47] proposed FAST & SIFT (algorithms in image matching) with triangulation to complete the localization. The results show the similarity between the actual route and the experimental route. The localization was feasible, but the algorithm depends on the corners of the ceil of the buildings; if there are no such feature points, that will lead to errors.

Navigation in the environment can be done using fuzzy navigation based on visual sensors or fuzzy navigation based on infrared sensors. When there is no information about the environment, the proposed method by [48] can achieve good results based on fuzzy logic specifications. The algorithm also needs to be tested in a complex environment.

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The uncertainty caused by the noisy readings from sensors for the vision-based robot (UAV) needs to be handled. Hence, the authors in [49] proposed a Non-Singleton Fuzzy Logic algorithm for SLAM that control the robot by handling the uncertainty. Experiments show that the new controller achieves better performance than the conventional PID controller.

Aerial robots or UAV (Unmanned Aerial Vehicle) has a problem coping with the spherical shell uniform distribution. The manipulation in (EKF) (Kalman Filter based) algorithm with the use of Gaussian Mixture Model (G.M.M.) (Fuzzy logic) can solve the problem as proposed by [50]. The reduction of parameterization and the observation of unnecessary landmarks improve the efficiency of the proposed method. Experiments show improvements in the correction stage of EKF only using radio-based range sensors.

In a narrow area, images will degrade, causing a pose estimation difficulty. VSLAM with feature matching method with the help of Inertial-Measurement Unit (IMU). Chen et al.[51] proposed a method called STCM-SLAM that uses tiling lines to extract image features. The performance of the approach compared to ORB-SLAM2 and OKVIS showed that the proposed method performed better. However, the method should be tested in dark and narrow places.

The dynamic objects decrease the traditional algorithms' performance due to the inference that happens when these objects intercept the robot's path. To treat better with dynamic objects, Dynamic-SLAM based on the ORB-SLAM2 algorithm was proposed by [52], by adding the SSD component. A deep learning-based object detector was also added to detect dynamic objects. The new method's accuracy was higher than that of ORB-SLAM2, PTAM, SVO, and LSD-SLAM as it achieved better dynamic object detection. However, the method needs more tests in more complex environments.

VSLAM compatibility with Robot Operating System (ROS) is crucial because some algorithms consume more CPU and GPU resources. Hence, Giubilato et al.[53] evaluated ORB-SLAM2, SPTAM, and RTAB-MAP by comparing their performance and the benefits of applying histogram normalization. ORB-SLAM2 and RTAB-MAP achieved the best performance in the test. However, the study recommended the inclusion of GPU in the experiment by editing the algorithms.

Most environments in the real world combine static and dynamic objects, which degrade SLAM algorithms' performance. To make robots recognize dynamic and static objects, the sparse motion removal (SMR) algorithm which is based on Bayesian networks has been proposed by [54]. In the algorithm, dynamic regions are eliminated, and static regions are fed into the VSLAM system. The results proved the method's efficiency, but the experiment needed to be performed in the real world.

Recognition of places is helpful in VSLAM algorithms because it makes the robot know where it is. To make SLAM algorithms recognize and store the knowledge about some places, the Neurologically Inspired approach was by [55] based on CNN. The approach worked with the localization algorithms to achieve good results, and the experiments proved the efficiency of the proposed method.

The problems in SLAM algorithms, such as consuming time and computation resources, trajectory drift, and the high cost of long-range LiDARs limit localization accuracy. For these reasons, ORB2 RGBD-SLAM is an improvement of ORB RGBD-SLAM proposed by [56] in which location estimation is done by a 3D camera instead of LiDAR to make the camera do a Virtual laser scan. Evaluations showed an improvement in the accuracy of the approach as it recorded small error ranges. However, the method should be tested outdoor to prove the image feature extraction.

When using laser sensor vision with IMU, errors are possible, especially when taking motion with significant angle changes. The problem can be solved by using RCNN (Recurrent Convolutional Neural Networks) using a 2D laser and IMU [57]. The enhancement can be a 3D laser with geometric methods. The results appeared with efficient pose estimation even with angular velocity compared with the traditional geometrical methods.

SLAM algorithms' accuracy issues can be solved by reducing the error in each step. Unscented Kalman Filter (UKF) with hybrid Adaptive Neuro-Fuzzy Interface System (ANFIS) was proposed for solving the issue of accuracy and landmarks state estimation [58]. The method was tested in complex and circular environments, and the results showed better accuracy due to error minimization in each step.

Automation of mobile robots depends not just on the SLAM algorithm, but there is a need for an algorithm to control the robot and avoid obstacles. Wang et al. [59] presented a method for the autonomous navigation of mobile robots. The method uses Particle Filter (PF) as a SLAM algorithm and Victor Field Histogram (VFH) (Fuzzy logic) for obstacle avoidance. The proposed method can reduce localization and SLAM errors according to the MATLAB simulation. Nevertheless, the method still needs to be tested on a real robot.

The authors in[60] proposed a system for mobile robot indoor navigation and collision-free path planning. The system uses an RGBD sensor and Probabilistic Road Map (PRM) algorithm (Fuzzy logic). The SLAM process is completed by the RGBD SLAM algorithm, and then, the map is converted to the Octo-Map algorithm to construct the map. The results show good indoor navigation performance, but the map constructed by the method was not good.

In large-scale dynamic environments, the accuracy and speed of the localization system get weakened due to the difficulty of treating dynamic objects in a large environment. Li et al. [61] proposed semantic segmentation of the image with the image morphology to process colored images and enhance pose estimation. The experiments showed a high-quality map represented by the algorithm and high SLAM accuracy.

The optimal path of mobile robots saves time and power; hence, achieving the optimum path was the goal of the algorithm proposed by [62]. The Hybrid Meta-Heuristic method combines Particle Swarm Optimization and Fringe Search algorithm (PSOFS). The results showed the ability of PSOFS to shorten, smooth, and save paths in an indoor environment.

Inertial Measurement Unit (e.g., wheel speed) is helpful in pose estimation; it is used with visual aspects to form Visual inertial SLAM. This measurement affects pose estimation; hence, Peng et al. [63] propose a method that depends on Monocular-inertial SLAM (Mono camera and Inertial Odometry). The results showed good indoor pose estimation, but the cumulative position error is 0.165 m (28 %). The computation of methods done by the nonlinear optimization method depends on the posterior probability (AI-based).

The presence of noise prevents the enhancement of an Extended Kalman Filter for real-time applications. Hence, Adaptive Extended Kalman Filter (AEKF) algorithm that uses Maximum Likelihood Estimation-Expectation Maximization (Fuzzy logic) MLE-EM was proposed by [64]. The results show that the method can be used when noise statics are unknown and there is system inaccuracy.

Tracking failure in VSLAM comes from the inability of the camera to detect image features because of the camera speed motion or low texture environment, or both. Hence, the authors in [65] proposed a method for VSLAM with bionic stereo cameras that can move flexibly with 3DoF. The method uses a Bundle Adjustment algorithm and the bionic eye to prevent tracking failure as proved in the experiments. However, the performance on dynamic and static objects was not determined.

In VSLAM, the drift of pose estimation comes from feature point tracking failure, especially with dynamic objects. As such, the author in [66]. proposed a method based on Semantic Segmentation

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with geometric constraint and Visual Inertial SLAM Mono (VINS-Mono). Indoor experimental results showed accuracy improvement, but outdoor results were not good.
Indoor environments consist mainly of walls and objects that can be considered landmarks for the localization process. The author in [67] proposed a method to make the usability of these landmarks in data association. The method is Semantic SLAM (RoomSLAM) which (AI-based) comes with an objects detector and walls detector. The results were compared to RGBDSLAM and the proposed method performed better.
The SLAM algorithms can be used off-road to estimate the position of the intelligent vehicles for auto-driven cars. Using a Mono camera may not be sufficient outdoor due to differences in image light or other parameters. Hence, Yang et al. [68] proposed a method with panoramic vision using multiple cameras that collaborate to share information of vision; the BA algorithm was also incorporated for localization. The results of the method are better than those of ORB SLAM and Multi-col SLAM.
SLAM algorithms make robots to percept their environment, and the perceptions need to be increased by increasing robot intelligence. ORB SLAM2 was improved in [69] to construct a 3D semantic map with semantic segmentation (AI). The proposed method was examined in the experiments and showed stability of pose estimation even with a low light scene. However, the semantic segmentation method needs more improvement.
Monocular VSLAM can be affected by the motion of the robot (velocity, sharp turning, and others) or challenging environments such as light and dark. Bruno et al. [70] proposed an algorithm combining Deep Neural Networks (DNN) and geometric VSLAM algorithms and called it Learned Invariant Feature Transformation (LIFT-SLAM). The efficiency of the new LIFT-SLAM was evaluated in both indoor and outdoor experiments, and the selected features were not the best in the image.
Visual odometry with a monocular camera gives poor performance and sometimes does not work in complex environments. VO is used with Deep Learning Neural Networks and a 6DoF Mono camera to build a navigation system [71]. The results showed that the proposed system is better than traditional methods but the camera movement may decrease the speed of localization.
Robots need SLAM algorithms to do their tasks perfectly; hence, Parra et al. [72] proposed and implemented an approach to do thermal insulation in underfloor voids by using an RGB-D sensor, laser scanner, and Point Cloud algorithm. Pose estimation was calculated by combining both laser scanner and RGB-D sensor data. The results showed successful position estimation compared to ICP, CPD, and NDT.
To present a heterogeneous system consisting of different sensors that prevent these sensors from falling over during the SLAM process, the authors in [6] proposed a method that represents a relationship between sensors using Bayesian Network with fuzzy logic. The experiments showed the efficiency of the proposed method and its better performance compared to an existing method in terms of enhancing the sensory system..
Sometimes, multi-robots are needed for a specific task; if the computation sources are costly, there is a need for a method to minimize the cost. Hence, Li et al. [73] proposed an approach for offloading cloud point computations with the help of RGBD-SLAM and modifying the ICP algorithm to FSHICP (Fitness Score Hierarchical Iterative Closest Point). Experiments showed decreases in the energy consumption of indoor multi-robot SLAM.
The authors in [74] reviewed the state-of-art VSLAM algorithms that use Artificial intelligence as a base for their work. The algorithms use neural networks like CNN, RNN, SIFT, and other algorithms

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that employ fuzzy logic. The study concluded that this field is helpful in SLAM and navigation algorithms.
Key frame-based SLAM algorithms have a problem of losing feature points of visual odometry. Therefore, ORB SLAM with Affine transformation was proposed in [75] to extract features of robot vision. A mathematical affine transformation then follows using Affine-ORB SLAM. The experiments showed a reduction in key-frame loss and high accuracy of localization. The method needs to increase the real-time accuracy by adding a laser sensor.
Path planning algorithms come after SLAM algorithms for the construction of the map of the environment. As such, the authors in [76] proposed a novel method for path planning in a global environment using a Generalized Laser Simulator (GLS) algorithm. Observed points are used to determine the barrier between the points through the border detection function. The proposed method proved its ability to find the optimal path in perfect time compared to the A* algorithm. However, the algorithm should be tested to find the local path with obstacle avoidance.
The noise from sensor readings is confused with the robot estimation in SLAM or task that depends on sensors. Ali et al. [77] proposed a novel algorithm for Active Force Control of a wheeled mobile robot named Laser Simulator Logic (LSL)(AI-based). The proposed method can determine the inertia moment during the robot trajectory, and the method can quickly eliminate noise from the sensor. Experiments show that the method effectively controlled the robot even in a zigzag circular environment and efficiently performed against noisy readings.
The difficulty of detecting and tracing dynamic objects in a static environment can impair VSLAM algorithm performance. ORB-SLAM2 with object detection algorithm based on Deep Learning with a probability model was proposed in [78] for reducing tracking errors; the experiments showed the method recorded better performance than RGB-D SLAM. Deep learning unsupervised and supervised should be specified to decide which is better to use with the method.
The Deep Learning VSLAM algorithm was proposed in [79] with Convolutional Neural Networks (CNN) to extract feature points. The feature points are hard to extract in texture-less environments, and feature point detection is helpful for pose estimation. The method proved to be efficient in real-time and can construct a 3D map. However, the real-time run comparison to the traditional algorithms is still insufficient.
Panoramic cameras with IMU were combined to trace wheeled mobile robots and construct the local map as proposed in [80]. The proposed method is PIW SLAM and can achieve high accuracy localization in all scenarios which are considered a challenge for traditional VSLAM. The results showed the robustness and high accuracy SLAM of the proposed method, indoor or outdoor, even with low light (low illumination).
Feature-based algorithms like RGB-D SLAM always cope weakly with dynamic objects in an environment assumed to be static. The DP-SLAM proposed by [81]. uses semantic segmentation and Bayesian probability theorem to detect the dynamic key points and pose estimation. The results demonstrate the performance of the proposed method, however, the motion removal is not good enough for map construction.
An unknown environment sometimes needs to be represented in a 3D map in SLAM, but this is not easy. To solve this problem, Kuo et al.[82] proposed the use of Virtual Reality VR to percept 3D maps from a 2D display. SLAM-based VR(AI-based) uses an RGB-D camera to scan the environment in real-time experiments. The results showed an error ratio reduced by the new method. However, the system should be equipped with other sensors.

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FastSLAM algorithm, which is based on particles, gets degraded due to the impairment of particles. This time, the solution to the problem comes with Hybrid Filter SLAM that uses Intuitionistic Fuzzy Logic System (IFLS) [83]. The proposed method increases accuracy by controlling the noise covariance matrix. The results proved that the proposed method performed better than FastSLAM for large environments.
The authors in [84] proposed an approach for SLAM with LiDAR with a low sampling rate, and at the start of each SLAM iteration, Relative Directional Neighbor Matching (RDNM) is applied. The proposed method depends on Point Set Registration (PSR) to solve the measurements' problem that can give different potentially significant position that changes the results. The experiments demonstrated the efficiency of the proposed method in solving the problem.
For robots to perform agricultural tasks in addition to industrial tasks, the authors in [15] proposed a robot system for fruit pick-up based on vision. The robot arm is 6DoF and equipped with a camera in hand. Localization is done by ORB-SLAM3 (AI-based) with a Stereo vision camera. The results demonstrated the SLAM accuracy of the proposed system. The AI-based localization algorithms can be classified based on the number of cited papers as shown in Fig. 4. Table 3 summarizes the comparison between the main localization features of the AI mentioned above algorithms.

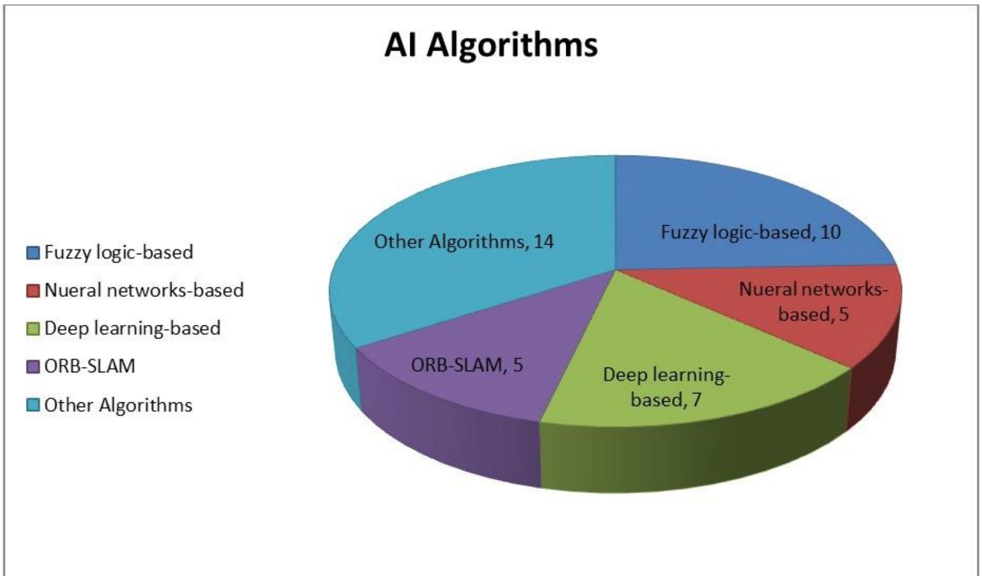

Fig 4. Show the classifications of AI-based algorithms

Table 3 comparison between AI-based localization

id	Author name	Algorithm	Environment type	Accuracy (error)	CPU time (speed)	Type of work
1	[46]	Fuzzy logic	indoor environment			Simulation
2	[47]	FAST & SIFT	indoor environment	~25(cm) in 500x250 (cm) trajectory		real-experiment

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3	[48]	fuzzy navigation based on infrared sensors	indoor environment	~9(cm) error in 100x50 (cm) navigation		Simulation
4	[49]	Non-Singleton Fuzzy Logic	Indoor unknown environment	~0.3 (m) error in the path of 3x3(m) trajectory	Speed 2m/s.	real-experiment
5	[50]	Gaussian Mixture Model (GMM)	indoor environments	localization error is 0.54(m) mapping error is 0.58 (m)	3000(ms) when using 50 beacons	Simulation and real-experiment
6	[51]	STCM-SLAM	indoor unknown environment	absolute trajectory error 0.008m	36.07(H) performance and CPU load is ~40%	Simulation and real-experiment
7	[52]	Dynamic-SLAM based on ORB-SLAM2	Dynamic environment	~1.25(m) path error 40x45(m) trajectory	38 (s) for complete trajectory	real-experiment
8	[53]	ORB-SLAM2, SPTAM, and RTAB-MAP comparison	unknown environment	ORB-SLAM2 error (~0.3m). SPTAM (0.5 m). (0.45) for RTAB-MAP	CPU usage ORB-SLAM2 (85%). SPTAM (98%). RTAB-MAP (98%)	real-experiment
9	[54]	Bayesian networks	Dynamic environment	Error for 2x1.5(m) trajectory is 0.1 (m)		real-experiment
10	[55]	The neurologically Inspired approach is based on (CNN)	Null	>3 (m) in place with area 700(m)		Simulation and real-experiment
11	[56]	ORB-SLAM	indoor large-scale environment	0.05(m) error	5(s)	real-experiment
12	[57]	RCNN (Recurrent Convolutional Neural Networks)	indoor environment	Error in the path ~2(m) in 30x30(m) trajectory		Simulation and real-experiment
13	[58]	(UKF.)with Adaptive Neuro-Fuzzy Interface System	unknown environment	mean square error is 0.0480(m)		Simulation
14	[59]	Victor Field Histogram (VFH)	unknown environment	Path error is ~0.25(m) in 10x10 (m) path		Simulation

15	[60]	Probabilistic Road Map (PRM)	indoor environment		2.82(s) for path (5.97m)	
16	[61]	semantic segmentation of the image	dynamic indoor environment	Path error ~0.05(m) in 2.5x1.5(m) trajectory	detect dynamic object in (56) ms	real-experiment
17	[62].	Particle Swarm Optimization and Fringe Search	Unknown Indoor Environment	0.53 the smoothness of the path		real-experiment
18	[63]	Monocular-inertial SLAM	indoor environment	cumulative position error ~0.165 m.	the runtime is 896.3 s 15 m ×15 m	real-experiment
19	[64]	Adaptive Extended Kalman Filter with MLE-EM	Null	Path error ~15(cm) in 500x600(cm) trajectory		Simulation
20	[65]	Bundle Adjustment	indoor low-textured and large-scale outdoor environment	LATERALLY error 0.129(m), VERTICALLY 0.033(m)		real-experiment
21	[66]	Visual Inertial SLAM Mono & Semantic Segmentation	Dynamic environment (indoor and outdoor)	Path error about ~6(m) in 60x60 (m) of trajectory in sequence 23	422.84 (ms) at each step	real-experiment
22	[67]	Semantic SLAM (RoomSLAM)	indoor environment	~3(m) error in the path in 40x40(m) trajectory		real-experiment
23	[68]	BA algorithm with panoramic vision using multiple cameras	dynamic off-road environment,	Path error by using three cameras is ~5(m) while using five cameras is ~4(m) in 60x60(m) trajectory	For five cameras and (264 map points), the median was 69.745(ms)	real-experiment
24	[69]	ORB SLAM2	indoor unknown environment	0.05(m) error	5(s)	real-experiment
25	[70]	Learned Invariant Feature Transformation (LIFT-SLAM)	unknown environment	ATE (m) 18.77. RPE (deg/m) 2.20. 700x300(m) trajectory		real-experiment
26	[71]	VO DL-Hybrid with Deep Learning Neural Networks	Unknown environment	~20(m) in trajectory 200x700 (m)	average run time per image 0.021(s)	Simulations

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27	[72]		Underfloor	No path or map just pose estimation		
28	[6]	Bayesian Network &fuzzy logic	indoor environment		Time is 2(s) in 1048 inferences for different network configurations.	Simulation and real-experiment
29	[73]	RGBD-SLAM &FSHICP	indoor environment	0.22 at 30 iterations (but no information about the path)	4510(ms) in 10 steps	Simulations
30	[75]	Affine-ORB SLAM	indoor and outdoor environment	The median of trajectory absolute pose error 0.352(m) 30x30 (m)		real-experiment
31	[76]	Generalized Laser Simulator	uncertain environment		~4(s) to reach the goal at the end of the path	Simulation
32	[77]	Laser Simulator Logic (LSL)	constrained environment & zigzag circular environment	a maximum tracking error of 10-6		simulation and real-time experiment
33	[78]	ORB-SLAM2 & probability model	dynamic environment	0.0752(m) Absolute pose error in 2x3(m).	67.08((ms/frame-1)	real-experiment
34	[79]	Deep Learning VSLAM& (CNN)	Unknown environment	maximum error is 0.055(m), minimum error is 0.002 (m) in 4x4(m) trajectory	~ 95 (ms) for each frame	real-experiment

3.4 Multi-Algorithm based Localization and comparisons

The comparison of three modern SLAM algorithms (TinySLAM, which depends on the Monte Carlo method (Statistical-based), GMapping SLAM algorithm that uses Rao-Blackwellized particle filter (RBPF) (Statistical-based), and Google Cartographer SLAM (based on AI)) was done by[85]. The results showed that Google cartographer has lower error dispersion while TinySLAM has error accumulation and GMapping has an asymptotic RMSE value to google cartographer..

Taketomi et al.[86] provided a survey from 2010 to 2016 of SLAM algorithms to summarize the recent VSLAM. They are classified into three classes - feature-based methods (MonoSLAM and PTAM), direct methods (DTAM, LSD-SLAM, SVO, and DSO), and RGB-D SLAM. However, MonoSLAM (Kalman Filter based) PTAM (AI-based) which uses bundle adjustment (BA) algorithm) was found better than MonoSLAM. The direct methods (DTAM) Ai-based) use the multi-baseline stereo to do the mapping. LSD-SLAM, SVO, and DSO are Ai-based, while RGB-D SLAM is Ai-based. The results showed that PTAM is better than MonoSLAM for the feature-based approaches while DTAM is the best for the direct methods, followed by LSD-SLAM; SVO and DSO can be considered spare for DTAM and LSD-SLAM.

The authors in [87] proposed a method for SLAM and navigation to solve the problem with a network of radio sources (Fuzzy logic approach). The method employs RSSI-based EKF-SLAM (Kalman Filter based); the errors of SLAM and navigation were satisfactory but the workspace was not big enough.

A brief survey of SLAM algorithms and their classification into collaborative VSLAM, filter-based approaches, and key-frame-based approaches was provided in [88]. Surveys are helpful to start working on some areas, especially when there are many algorithms in the area.

SLAM and navigation are needed to make robots navigate and move autonomously and do other tasks; most tasks are in dynamic environments. Rehman et al. [89] compared three common SLAM algorithms (GMapping (Statistical-based), HectorSLAM (Statistical-based), and Cartographer (Ai-based) with LiDAR as a laser pointer) for navigation. According to the experiments, the computations and memory cost of GMapping are high, grid map's performance increased with HectorSLAM, and Cartographer is suitable for indoor environments.

The object detection process is remarkable in SLAM and navigation to avoid obstacles in the environment. The authors in [90] reviewed state-of-art algorithms that use object detection techniques. SIFT and SURF, for example, for indoor image-based object detection methods use histograms for indoor localization, such as FAST and ORB SLAM.

SLAM algorithms classifications have many forms according to the main purpose of the algorithm. Taheri et al. [91]] classified SLAM algorithms that use filters into Kalman Filter based, tree-filters-based, information-filters, and particle filters. The study noted that Kalman filters were more accurate when there is uncertainty, but they are slow.

Analyzing different approaches to SLAM and studying the challenges of controlling a robot with historical scenarios was the goal of the study [92]. The review classified the methods into probabilistic approaches (Markov, Kalman Filter, U.K.F., EKF), evolutionary approaches (PSO, and GA-Fuzzy logic-based EKF), and RFID-based approaches. The conclusion was that using EKF in an environment with low noise, and the combination of EKF and one of the evolutionary approaches, will increase the efficiency of SLAM. Finally, RFID was found to be better for use in limited environments.

The localization algorithms reviewed in this paper can be classified based on the number of cited papers, as shown in Fig. 5.

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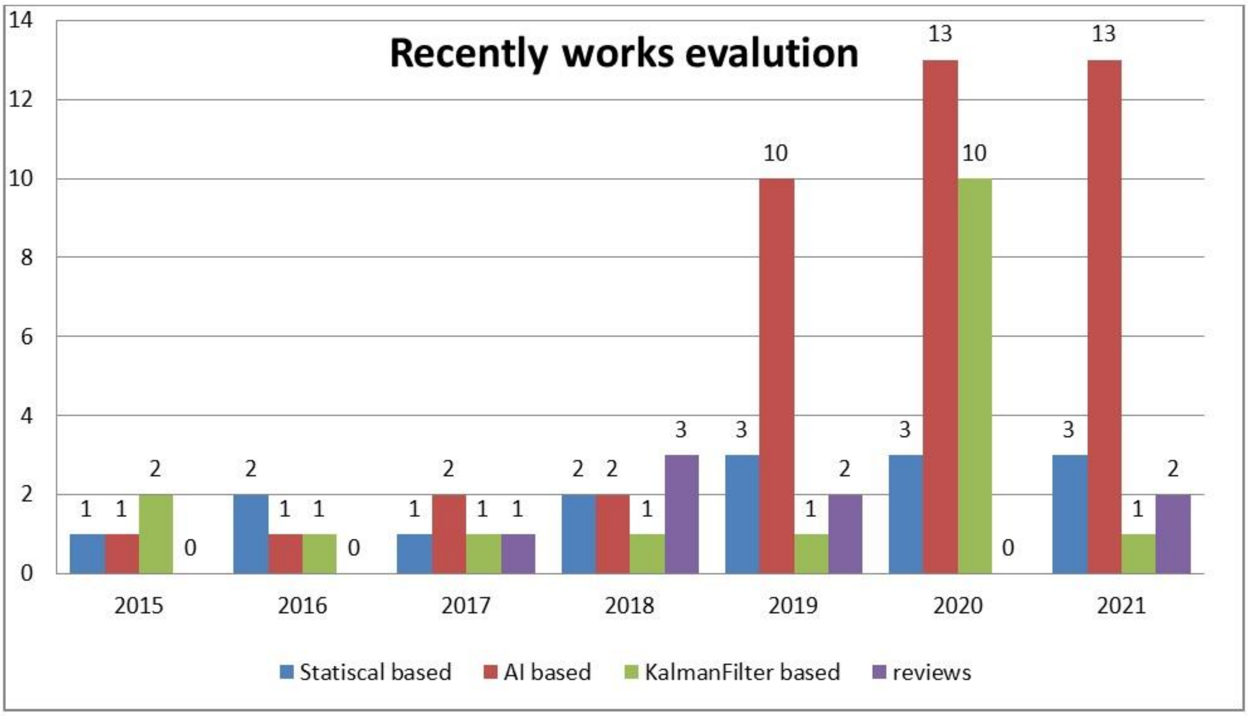

Fig 5. The localization algorithms reviewed in this paper basing on the number of cited papers

4 Conclusion

This paper reviewed the most recently published works for position estimation of mobile robots during Simultaneous Localization and Mapping (SLAM) for the period 2015 to 2021. After reviewing previous research, we have categorized the algorithms according to their computational performance in the estimation of the location and mapping. Thus, these algorithms have been classified into three groups, namely, Kalman Filter, Statistical algorithms, and Artificial Intelligence. We found that algorithms based on the Kalman filter are not efficient enough in noise processing and have become rarely used in the past years. Statistical-based algorithms are also starting to be neglected but are often combined with other methods to improve their performance. The most useful algorithms in statistical algorithms are those that depend on particles (particle filters). The AI-based methods have been widely used in the past three years because their computational time is low and requires less processing than the methods that depend on the Kalman filter. AI-based methods can be further classified based on their computations; for example, Fuzzy logic-based algorithms come at the forefront of the most used aspect because they deal with noise better than other algorithms; then, there are deep learning algorithms and neural networks algorithms. The common sensors used in the previous works are camera, IMU, LiDAR, LRF, Ultrasonic, RFID, and wideband work, which are varying according to the type of the environment and work. For example, a Camera with IMU is mostly used for outdoor environments where the luminance is good, while LiDAR or Laser Range Finders performs well when the luminance is low. Some types of environments need a specific type of sensor, such as a glass-walled environment that reduces the accuracy of LRF or the underground environment, which needs a Laser Scanner (e.g., LiDAR). Despite these, the noise problem is still not wholly resolved. Laser Simulator Logic (LSL) algorithms, used in Active Force Control of Mobile robots, perform very well against noises. Our future direction will be to use the LSL algorithm in the Simultaneous Localization and Mapping of Wheeled Mobile Robots.

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