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A Survey of SLAM Techniques: From Classical Approaches to Deep Learning-Based Methods

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Abstract. Robotics is a prominent and rapidly evolving field in modern society. Various sorts of robots have been developed by scientists for different situations. However, these robotic systems cannot operate without addressing a critical component: path planning. Simultaneous Localization and Mapping is an algorithm that serves as a pivotal component in the whole pathway planning process. Robots rely on this algorithm to construct a real-time environmental map within their internal systems. In this way, robots can create the routes with high precision and high operational efficiency. Since its inception, SLAM has quickly become a core research direction in the global robotics industry. After years of development, numerous SLAM algorithms serve for sophisticated conditions and different sorts of robots. This article provides a comprehensive review of the evolutionary trajectory of SLAM and highlights the current mainstream research directions, including Feature-based SLAM, Sensor Fusion SLAM, and Learning-based SLAM. Future challenges and development trends of SLAM are also discussed.

Keywords: SLAM algorithm, robotics, robot navigation, sensor

1. Introduction

Nowadays, robots have emerged as primary tools for enhancing productivity. People need robots to assist in tasks such as surveying, manufacturing, and operations in harsh environments. Numerous enterprises and research institutions are engaged in robotics research and development. Boston Dynamics, for example, is a well-known entity that develops highly advanced robots renowned for their exceptional mobility, balance, and human- or animal-like locomotion. The products from this company are widely utilized in industrial inspection, public security, scientific research, and logistics. Against this backdrop, a variety of robotic systems have been developed to cater to the requirements of complex tasks and objectives. Robotics is an area with the creation of operations and sophisticated algorithms. To manage different types of robots, the Robot Operating System (ROS), which is an open-source platform, handles the various mechanisms efficiently. In each project, streamlining project-level programming to reduce complexity is also a key aspect of robotics research. Simultaneous Localization and Mapping (SLAM) is a core algorithm for robots, enabling simultaneous map construction and self-localization [1]. Prior to the development of this algorithm, the mapping and localization were basically separated. Robots had to rely on pre-existing maps or real-time online maps for path planning. At that time, robots primarily relied on absolute

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localization or dead reckoning techniques. For the absolute localization, infrared reflection devices were typically installed in the surrounding environment, limiting the flexibility of robotic applications. For dead reckoning, the errors tend to accumulate during navigation, causing the robot to deviate from its target position [2]. In these processes, robots lacked autonomy and intelligent planning capabilities. The element of dynamic condition was not considered in this process, which results the low accuracy and efficiency. In an unknown environment, robots need to locate themselves and ensure a stable platform for all operations. SLAM serves as a fundamental technology for exploring environments that are inaccessible or uncharted by humans. In this way, robots can not only navigate on the confirmed track, but also move in the unknown environment and develop their own pathway.

Fundamental innovations and progressive advancements in SLAM have primarily focused on addressing four key questions. 1) Does this algorithm provide a map for robots while navigating? 2) Is this algorithm possible to apply to all sorts of situations? 3) Is the new approach stable enough for deployment across multiple types of robotic hardware? 4) Are there innovative design concepts integrated into the algorithm? This literature answers these questions really well, and this is also a great opportunity for people to learn the progressive process and innovation, and the logic of the SLAM approach. Additionally, this paper categorizes various SLAM algorithms into distinct categories, each with its own advantages and limitations. Some specific SLAM approaches can only be applied to particular circumstances.

Based on this, this paper is structured into five main sections. First of all, the main idea and classification of SLAM will be introduced. Secondly, it analyzes and elaborates on the evolutionary process of SLAM. Finally, it summarizes the key future research directions by drawing on relevant literature.

2. Background

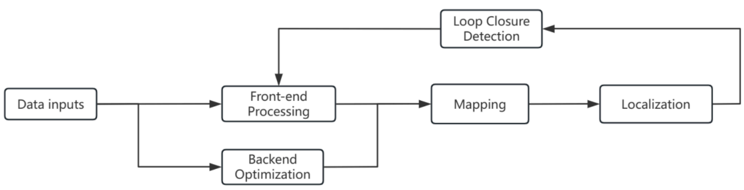

Figure 1. SLAM basic flow

Basically, a complete SLAM mapping workflow is illustrated in Figure 1 [3]. Firstly, data from cameras or LiDAR sensors will input into the system. The data set will be then split into the front-end and the back-end. In the front-end, the algorithm will calculate the 3D pose change, while the back-end optimize images. During mapping, different mapping strategies are employed based on specific scenarios. The final step is the localization, where the robot determines its current position and proceeds with path planning and other tasks. There is a loop closure detection to ensure the accuracy of the map

2.1.1. Visual SLAM

Visual SLAM Approach constitutes a major branch of the SLAM field. It primarily relies on visual sensors for data acquisition and is classified according to the type of camera used—namely monocular, binocular, and RGB-D cameras . Firstly, the Monocular Visual SLAM is the most

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lightweight and straightforward approach. The use of monocular camera supports the whole mapping process and provide video information [4]. The smaller video data repository reduces hardware requirements, resulting in relatively low costs for Monocular Visual SLAM [5]. However, a monocular camera cannot independently perceive depth information from images, it relies on the movement of the camera to complete depth information, which compromises the accuracy of the constructed map [6]. In this context, Monocular Visual SLAM always be used assisted with other sensors, odometers for instance. Secondly, the RGB-D Visual SLAM. This method uses RGB-D camera to detect surrounding environment. This camera captures both color information and depth data for each pixel [5], allowing the algorithm to directly determine the 3D coordinates of objects. Because of the huge amount of the points cloud, the hardware requirement for this algorithm is pretty high [7], leading to higher overall system costs. Thirdly, the Binocular Visual SLAM. Just as its name implies, the binocular camera be used as the main sensor to absorb data. This camera is essentially two monocular cameras integrated into a single system. The system uses parallax principles to calculate the depth of objects in the image, analogous to human binocular vision. Unlike RGB-D SLAM, Binocular Visual SLAM obtains image depth information through computation, while RGB-D SLAM directly obtains it from the surrounding environment [5]. There is a formula for Binocular Visual SLAM:

$$\mathrm{Z} = \frac{\mathrm{f \cdot B}}{\mathrm{xL - xR}} \tag{1}$$

Z represents the depth, the distance between the camera and the object. f denotes the focal length of the camera. B is the baseline, the horizontal distance between the centers of light of the left and right cameras. xL, xR are the horizontal pixel coordinates of the object projected onto the left and right images, respectively. Under these circumstances, RGB-D SLAM will be easily affected by lighting conditions, making this algorithm more widely used in indoor environments, such as on robotic vacuum cleaners. In contrast, Binocular SLAM is less affected by such factors, particularly in high-light environments.

2.1.2. Lidar SLAM

Radar SLAM represents another key category within the SLAM framework. It relies on distance data captured by LiDAR sensors to accomplish map construction and self-localization. The whole Lidar SLAM system contains data collection, feature extraction and matching, pose estimation, map updates, and closed-loop detection [8]. When the lidar sensor is working, it will calculate the time interval between the laser being emitted and received, which makes the construction of the point cloud [9]. This point cloud replaces image data to compute the robot's position and construct an environmental map. Compared with Visual SLAM, Lidar SLAM can avoids instability issues encountered under complex lighting conditions. After the construction of the point cloud, the robot executes feature point matching and map construction. The advantages of Lidar SLAM are really obvious. The characteristics of lidar can enlarge the detection range with strong robustness. In this case, a Lidar SLAM system can operate consistently whether in harsh weather or illumination-deficient environments. To meet the requirements of operating in diverse environments, the rotating mechanisms and optical components of LiDAR require high precision, leading to high manufacturing costs. Additionally, a 3D lidar sensor will generate a point cloud with millions of information. For example, a 64-channel LiDAR sensor can generate over 1 GB of data per second. Moreover, feature point matching must be completed within milliseconds, which poses a significant challenge for hardware performance. For the contemporary industry, the Lidar SLAM algorithm is

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always used in complex circumstances. In the automobile and robotic vacuum cleaner, this branch of the SLAM algorithm is always used to generate an accurate map of the surrounding environment to avoid accidents.

3. Classification of SLAM approaches

With the development of robotics, researchers have recognized that SLAM algorithms play a pivotal role in the robotics industry. A multitude of SLAM variants have been developed to meet the needs of different robotic platforms and application objectives [10]. The evolution of SLAM can be divided into four distinct stages: Fundamental SLAM, Incipient SLAM, Modern SLAM, and Future (Learning-based SLAM). Figure 2 is about the representative literatures to demonstrate different stages of evolution.

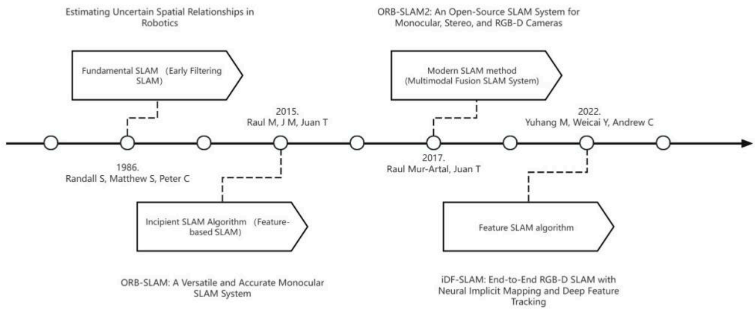

Figure 2. Development of SLAM

3.1. Fundamental SLAM

The earliest SLAM algorithms emerged in the 1980s. However, until 1986, the earliest mathematical expression was first proposed, which be demonstrated in Figure 2. In the thesis of 'Estimating uncertain spatial relationships in robotics (Smith, 2013) [2]', the authors provide a comprehensive derivation of the mathematical equations underlying SLAM, which can be regarded as the foundational innovation of the SLAM algorithm. The most significant contribution of this work is the integration of mapping and localization into a simultaneous process. Using of matrix to give the mathematical expression for the SLAM algorithm. Additionally, the paper presents an experimental case to validate this mathematical formulation in a real-world scenario. Basically, there are four steps for the experience: (1) The robot senses the object (#1), (2) the robot moves, (3) the robot senses an object (#2) which it determines cannot be object (#1), (4) trying again, the robot succeeds in sensing object (#1), thus helping to localize itself, object (#1), and object (#2). This experience successfully validates the core logic of SLAM, marking it as a landmark innovation in that era.

3.2. Incipient SLAM algorithm

After the proposal of the basic SLAM algorithm, numerous variants have emerged. During this period, SLAM transitioned from theoretical exploration to practical application. A wide range of sensors were integrated into SLAM systems, including lidar, monocular camera, binocular camera, gyroscope, and odometer. This integration significantly improved the accuracy and feasibility of SLAM. Figure 2 presents the literature of 'ORB-SLAM: A Versatile and Accurate Monocular SLAM System (Raul et al. 2015) [4]', the author proposes the most essential algorithm in this stage. Driven by hardware advancements at the time, ORB-SLAM initially adopted a monocular camera as its

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primary sensor (the development of ORB2-SLAM extends to use a binocular camera and RGB-D camera). This approach utilizes ORB (Oriented FAST and Rotated BRIEF), which minimizes the time consumption for feature point extraction. The main procedure is divided into three parts: tracking, local mapping, and loop closing. Furthermore, the open-source release of ORB-SLAM has contributed significantly to the evolution of SLAM technology.

3.3. Modern SLAM method

Modern SLAM is characterized by support for multi-sensor fusion, semi-dense mapping, and loop closure optimization. Besides utilizing multiple primary sensors for data acquisition, auxiliary sensors are integrated to enhance mapping accuracy. ORB-SLAM2 is the most representative algorithm of this stage and is highlighted in Figure 2. In 'ORB-SLAM2: an Open-Source SLAM System for Monocular, Stereo and RGB-D Cameras (Raul Mur-Artal and Juan D. Tard' os, 2017) [5]', the authors present an enhanced version of the original ORB-SLAM. The basic framework is still divided into three parts, but the development makes multiple data sources available. It is the first open-source SLAM system to support monocular, binocular, and RGB-D cameras. Additionally, this approach lays the foundation for the subsequent ORB-SLAM3 (with IMU and multi-map support).

3.4. Learning-based SLAM

Basically, the learning-based SLAM algorithm is widely regarded as the future direction of robotic mapping and localization [11]. Multiple learning-based approaches added into the SLAM mapping process can improve the intelligence, which can affect the stability and efficiency indirectly. Learning-based SLAM enables algorithm lightweighting. For instance, in Lidar SLAM, semantic information can replace part of the point cloud data, which decreases the size of the whole process significantly. In Figure 2, 'iDF-SLAM: End-to-End RGB-D SLAM with Neural Implicit Mapping and Deep Feature Tracking [7]' is highlighted as a representative learning-based SLAM algorithm. In general, iDF-SLAM is a feature-based front-end SLAM algorithm that supports online training. As a result, this design enables it to demonstrate competitive tracking accuracy and efficiency.

4. Challenges and future

The future development of SLAM holds substantial potential. With the influence of developing AI, future SLAM systems will become increasingly intelligent [12]. However, current SLAM still faces challenges related to accuracy, reliability, algorithm lightweighting, and hardware requirements. For solving these problems, robustness in a dynamic environment is an essential element. After that, future robotics will focus on robot collaboration, which means scientists need to consider controlling many robots at the same time. The Collaborative SLAM algorithm needs to be invented.

4.1. Robustness in dynamic environments

Robotic navigation often occurs in environments that undergo frequent dynamic changes. Unforeseen events can occur instantaneously, which requires a low latency of the whole system. In this way, the map and the pathway need to change actively to adapt to the changing obstacles.

There are two basic ways to achieve this. The first one is to advance hardware. The combination of deep learning and SLAM algorithms can not be achieved in low computing power environment. However, sophisticated algorithms often demand high-performance hardware [13], which may

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increase system costs or result in bulky form factors. Second, researches can develop methods to simplify the mapping process. In this way, the algorithm will be designed as a sparse mapping. This approach will not create dense mapping, only retain key frames. Robots only need to estimate poses and maintain a small set of map points, eliminating the need for large-scale point cloud reconstruction.

Recent advancements in AI have also enabled the integration of AI techniques to enhance SLAM robustness. In the SLAM process, AI can help with feature point extraction and pose estimation. HF-Net is a potential neural network to help with feature point extraction [14]. For pose estimation, a CNN architecture can make the position more precise. Also, Semantic SLAM is a potential domain. The Yolo network can be used in this method to provide semantic information for the mapping process, eliminating the need for robots to generate full point clouds and simplifying the SLAM pipeline. Nonetheless, the integration of AI into SLAM still requires further development.

4.2. Collaborative SLAM

With the demand for multiple robot navigation, has driven the need to extend SLAM to support multi-robot collaboration. In multi-robot systems, each robot generates an individual map, making the alignment accuracy of map features a critical concern. The core challenge for the collaborative SLAM algorithm to solve is multi-vehicle communication. The accuracy and robustness require very smooth communication. Under this circumstance, collaborative SLAM (C-SLAM) algorithms must be lightweight. Basically, the developing trend in C-SLAM is decentralized or distributed architectures, which enable the algorithm to utilize data from all robots in the group for mapping and path planning [15].

5. Conclusion

With the development of cutting-edge technology, numerous new SLAM variants have emerged. Each stage of SLAM development has aimed to enhance the algorithm's robustness and accuracy. Additionally, some emerging SLAM variants are tailored to specific application scenarios. In the introduction, this article states four questions for SLAM evaluation. For the first question proposed in introduction, whether the most privative SLAM or the newest SLAM appropriately solved this problem. Basically, this is the main goal of what the SLAM algorithms. For the second question, depending on the different categories mentioned in this article, each type of SLAM algorithm has its own concentration. For example, LiDAR SLAM is really suitable for a dark environment but requires expensive sensors compared to binocular SLAM. Binocular SLAM, meanwhile, can generate highly accurate maps in well-lit indoor environments. Most of the new categories of SLAM are stable. As the paper mentions in the last point, each SLAM approaches have its aims, which make them operate in different situations. As for the stability, it's not only related to the quality of the algorithm, but also depends on the capacity of the hardware. A clear trend is pursuing algorithm lightweighting, which lowers the requirement. The answer to the last question is yes. After the original SLAM approach was invented. Innovative concepts have been continuously integrated into SLAM: Since the advent of basic SLAM, researchers have integrated novel ideas and methods—most notably in learning-based SLAM. Deep learning, which simulates the neural network structure of the human brain, represents one of the most innovative advancements in SLAM

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