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Simultaneous Localization And Map Building – A Guided Tour

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Abstract- **Simultaneous Localization and Mapping (SLAM) has been one of the active research areas in robotic community for the past decade of years. SLAM addresses the problem of a robot navigating and building a map of an unknown environment, without an initial map or an absolute localization means. This paper attempts to provide a comprehensive overview of the SLAM problem. Successful SLAM implementations using laser, sonar and radar can be found in the literature. However, recent extensions to the general SLAM problem has looked into the possibility of using 3-dimensional features and the use of vision sensors. We will focus on these two approaches to the SLAM problem using vision: one with single or monocular camera and another with stereovision. Current applications and future challenges will also be discussed.**

I. INTRODUCTION

In the practical application of an autonomous robot, the first encountered problem is localization. The ability to construct a map or floor plan while localizing in it is crucial in order to accomplish many tasks. For example, a delivery robot needs to know its position and orientation relative to its starting point in the map to successfully navigate through an office area. Although the localization problem could be easily solved by using a global positioning system such as a satellite-based GPS (Global Positioning System), such global sensors are restricted to only a certain robot environment. GPS technologies cannot function indoors or in an obstructed area. Furthermore, the existing GPS network provides accuracy to within several meters, which is also unacceptable for the purpose of localizing smaller-scale mobile robots.

It has been understood early in the robotic community that the mapping and localization of the mobile robot are dependent. In fact they are generally seen as two facets of the same fundamental problem and cannot be obtained independently of one another [1]. Having just the spatial position and orientation of the robot is not sufficient, a successful autonomous mobile robot must also interpret data from the on-board sensors, such as vision sensor, laser sensor, sonar, code disk, etc. to build up a geometrical and/or topological model of the environment. The simplest approach to map building relies on the robot location estimates provided by dead-reckoning. It is simple, inexpensive, and easy to implement in real time, but it is also well known that dead reckoning techniques generate position estimates with unbounded error growth.

The term, Simultaneous Localization and Map Building (SLAM), Originally introduced by Cheeseman et. al. [2],

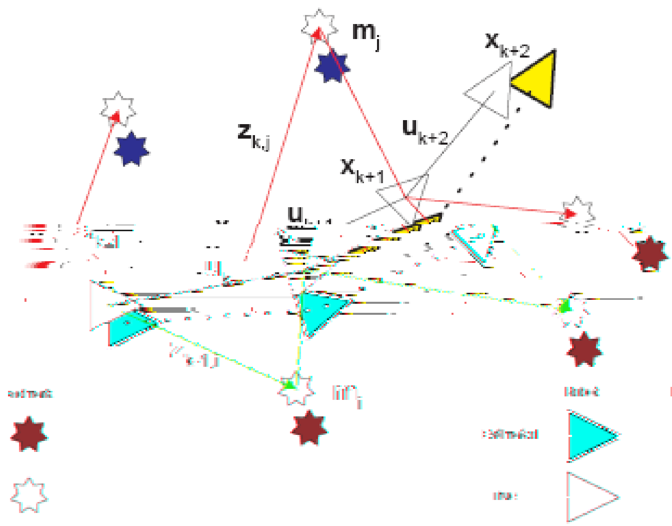

Fig. 1. The essential SLAM problem. [3]

II. SLAM PROBLEM

In the basic SLAM process, consider a mobile robot moving through an environment. It executes a motion and estimates its new location using odometry. It then takes relative observations and extracts geometric features from the raw sensor data. The SLAM problem is to estimate the position of the robot together with the locations of all the features as shown in Fig. 1.

At a time instant k, the following quantities are defined:

- $\mathbf{x}_k$: The state vector describing the location and orientation of the mobile robot.
- $\mathbf{u}_k$: The control vector, applied at time k-1 to drive the mobile robot to a state $\mathbf{x}_k$ at time k.
- $\mathbf{m}_i$: A vector describing the location of the i^{th} landmark whose true location is assumed time invariant.
- $\mathbf{z}_{ik}$: An observation taken from the mobile robot at the location of the i^{th} landmark at time k. When there are multiple landmark observations at any one time or when the specific landmark is nor relevant to the discussion, the observation will be written simply as $\mathbf{z}_k$.

In mathematical terms, the objective of SLAM is to estimate the state vector $\mathbf{x}_k$ and the location of all the features, at discrete time instant k. For this, the observation data from the sensors are constantly sampled and a map is built while the location of the robot is updated immediately as it is traveling through the environment. In this formulation, the localization and mapping are performed simultaneously.

In recent years, the SLAM problem has attracted wide attention by the mobile robotics community and many new algorithms and techniques have been developed. Despite significant progress in this area, substantial issues remain in practically realizing a more general solution to the SLAM problem. There are also cases where SLAM was employed in unmanned aerial vehicles [4, 5] and autonomous underwater vehicles [6]. However, despite of its success in practical applications, the problem of SLAM still presents some difficult issues, including the related problems of computational complexity, data association and environment representation.

III. SENSORS IN SLAM

Sensors are the fundamental robot input for the process of map building. The characteristics of the sensors and the degree to which sensors can discriminate the world state are therefore critical. In order to create a map using sensors, such as ultrasonic range, it is necessary to consider the following important steps: sensor interpretations, integration over time, pose estimation, global grid building, and exploration [7].

For indoor robots in particular, the SLAM problem was initially addressed mostly using sonar. Durrant-Whyte et. al., [8] have implemented systems using a wide range of vehicles and sensor types and are currently working on ways to ease the computational burden of SLAM. Chong and Kleeman [9] achieved nice results using advanced tracking sonar and accurate odometry combined with a submapping strategy.

Laser sensors provide more accurate 2D depth data in real-time (extendable to 3D with additional servo drive), and many SLAM-related algorithms have been devised based on data obtained specifically from laser range finders. Ian and Stefan [10] present an approach to the generation of three dimensional maps that exploits improvements in vehicle location estimation by the SLAM algorithm using laser range finder. In a similar work, Brenneke et. al., [11] implemented the laser sensors in outdoor environments. The idea was to combine 3D perception with 2D localization and mapping to allow autonomous navigation in uneven and hilly environment, but without the computational costs of full 3D modeling. Castellanos et. al., [12] went on further by taking advantage of a multisensory system formed by two different sensors. A laser range finder and a CCD camera were fused to increase their robustness and assure reliability and precision of the observed features. The group also proposed a mapping strategy called the SPmap, a probabilistic framework for the SLAM problem [13]. Sensors such as laser and sonar rings for range measurement have been traditionally used to solve the SLAM problem. Recently, vision-based systems have also gained a great interest in the robotics community. Nevertheless the use of the auditory sensing in solving SLAM has not been much explored. Munguía et. al., in their work [14, 15], focus on the inclusion of the hearing sense in SLAM. Without a priori information of the sound source location, as the robot moves, the position of the sound source and the robot position in a global coordinate frame are both estimated.

A. Sensor Noise

Sensor noise induces a limitation on the consistency of sensor readings in the same environmental state. It is a difficult task for the robot to capture all the environmental features and project them on the map. These missing or overlooked data are often the source of sensor noise problem. It is because of the inaccuracy and incompleteness of these sensors that poses difficult challenges.

Consider a sonar transducer which emits sound toward a relatively smooth and angled surface, much of the signal will coherently reflect away, failing to generate a return echo. A small amount of energy may return eventually depending on the material of the object. From the robot's perspective, a virtually unchanged environmental state will result in two different possible sonar readings.

In another example, a vision system used for indoor navigation in an office building may use the pixel intensity values of landmarks detected by its camera as features. However, the features selected are dependent on the illumination of the building's interior. As a result, the camera appears noisy from the robot's perspective as if subject to random error, and the features obtained from the camera will not be usable, unless the robot is able to execute a more robust feature detection algorithm. Such scenario is only one example of the apparent noise in a vision-based system. Picture jitter, signal gain, blooming, and blurring are all additional sources of noise, potentially reducing the useful content of a captured image.

Sensor noise reduces the useful data content from the sensor readings. An alternative is to take multiple readings into account, employing temporal fusion or multi-sensor fusion to increase the overall information content of the robot's inputs.

IV. VISION-BASED SLAM

Wide availability of low cost, low power and light-weight cameras as well as maturity of computer vision algorithms have made real-time vision processing much more practical in recent times, and consequently there has been an increasing interest in visually based navigation systems in the robotic research community. Cameras are interesting as they provide to obtain an accurate and detailed 3D representation of the environment, as well as perceptual information such as textures and colors, which can be matched by few other sensors.

Performing SLAM based on visual perception has a number of advantages over traditional methods which deploy laser, sonar and other sensors: First, it provides data perceived in a solid angle, allowing the development of 3D SLAM approaches in which the robot state is expressed by 6 parameters (3D translation, roll, pitch, yaw). Second, visual motion estimation techniques can provide very precise robot motion estimates. Finally and more importantly, very stable features can be detected in the images, yielding the possibility to derive algorithms that allow matching them under significant viewpoint changes. Such algorithms provide robust data association for SLAM.

Both monocular and stereo pairs have been used for mobile robot's vision-based mapping and navigation. The goal is to autonomously explore an unknown environment and build a consistent map with an accuracy that is competitive with active range sensing solutions.

A. Bearings-only SLAM

The bearings-only SLAM problem is an instance of the more general partially observable SLAM, in which the sensor does not contain enough information to determine the location of a certain landmark. Using sonar sensors, for example, raises the problem of range-only SLAM. A solution to this problem has been proposed by Leonard et. al., [16] since a single observation is not enough to estimate a feature, multiple observations are combined from multiple poses.

Several contributions propose different solutions for delayed initial state estimation in bearings-only SLAM [17]. Bailey, in his work [18], proposes an estimation which is computed using observations from two robot poses, and is determined to be Gaussian using the Kullback distance. The complexity of the sampling method proposed to evaluate this distance is quite high. A combination of a Bundle Adjustment for feature initialization and a Kalman filter are proposed by Deans et. al., [19]. The complexity of the initialization step is greater than a Kalman filter but theoretically gives more optimal results. Davison and Murray made the first application of active vision to real-time, sequential map-building within a SLAM framework [20]. A similar method based on a particle filter to represent the initial depth of a feature is proposed by Davison in [21]. However, its application in large scale environment is not straightforward as the required numbers of particles are linear with the initialization range. In another work, Davison et. al., [22] implemented localization and mapping with one wide-angle camera for any kind of robot. In [23], since the initial Probability Density Functions (PDF) of a feature is approximated by a sum of Gaussians, bad members are pruned until only a single Gaussian remains, that is then simply added to the Kalman stochastic map. A first un-delayed feature initialization method was proposed in [24]. The initial state is approximated with a sum of Gaussians and is explicitly added to the state of the Kalman filter. The sum of Gaussians is not described and the convergence of the filter when updating a multi-Gaussian feature is not proved. This algorithm has been recently extended in [25] using Gaussian Sum Filter. Also, a method based on a Kalman federate filtering technique is described in [26]. Bearings-only SLAM using vision is very similar to the well known Structure from Motion (SFM) problem. In [27], a framework for visual SLAM is presented based on a SFM approach from multiple views.

A recent work by Pangercic et. al., [28] have demonstrated an unique measurement model that consists of the combination between the Region of Interest (ROI) feature detector [29] and the Zero-mean Normalized Sum-of-Squared Differences (ZNSSD) feature descriptor [30]. They both demand very little computational cost while still remaining invariant to translations, rotations and scale. By adapting monocular SLAM and particle filter to the planar mobile robot, the navigation performance is enhanced compared to the encoder only system [31].

Bearing-only SLAM is a partially observable SLAM problem, in which the sensor cannot directly retrieve depth information from the scene, but only the bearings of the features are observed. It requires a dedicated landmark initialization procedure, which integrates several observations over time.

B. SLAM with Stereovision

Stereopsis or Stereoscopic vision is the process of perceiving depth or distances to objects in the environment. As a strand of computer vision research, the stereo vision algorithms have advanced noticeably in the past few decades to a point where semi-commercial products are available as off the shelf devices. However a more augmented approach is needed to realize a sensor useful in SLAM. A schematic of the components along with interactions amongst each other is outlined in Fig. 2.

Basic algorithms used in the approach include stereovision, interest points detection and matching, and visual motion estimation. Because localization is a key issue in SLAM, many systems rely on identifying features for matching between images. One well-known approach is SIFT (Scale-Invariant Feature Transform) developed by Lowe [33]. An approach that uses SIFT is implemented by Se et. al., [34] with results obtained by a robot evolving in 2D in a $10 \times 10m^2$ laboratory environment, in which about 3500 landmarks are mapped in 3D. Another popular algorithm for registration data sets is the Iterative Closest Point (ICP). The ICP is based on searching of nearest point-to-point, point-to-tangent plane pairs and point-to-projection, and additionally estimating the rigid transformation which aligns them. The main of arduous computing part of ICP is an exhaustive search for correspondence and matching two image frames afterward [35]. Kyun Jung et. al., [36] presented a SLAM approach based on an Extended Kalman Filter (EKT), using only a set of non-registered stereovision image pairs.

There are two popular frameworks in the SLAM community, the EKT and the Rao-Blackwellised Particle Filter (RBPF). The latter was chosen by Elinas et. al., [37] in constructing accurate dense metric maps of 3D point landmarks, and 2D occupancy grid maps from dense correlation-based stereo. Sim et al., [38] firstly presented stereo vision based SLAM using the FastSLAM algorithm, but his global SIFT feature matching influences the processing velocity seriously. Sim and Little, [39] then addressed the problem of exploring and mapping an unknown environment using a robot equipped with a stereo vision sensor. RBPF is also implemented to solve the SLAM problem and uses efficient data structures for real-time data association, mapping, and spatial reasoning. Similarly, Congdao et. al., [40] present an algorithm using a stereo camera based on RBPF in unknown outdoor environments.

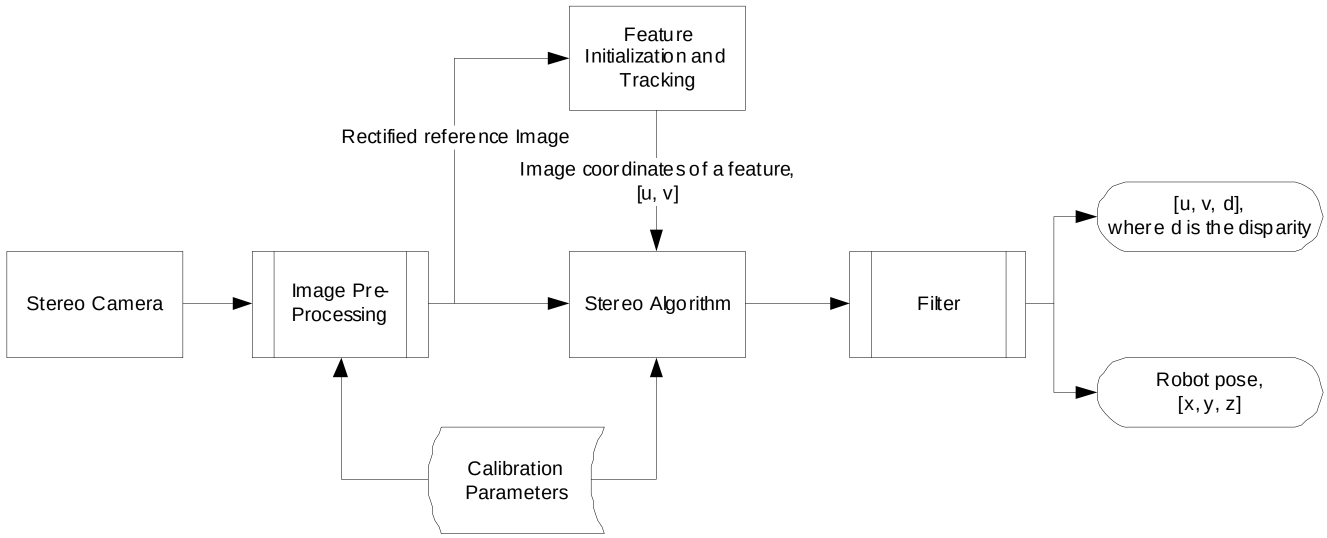

Fig. 2. The vision system for a SLAM implementation [32]

V. REPRESENTATIONS IN SLAM

The problem of representing the environment in which the robot moves is also a problem of representing the robot's possible position or positions. Decisions made regarding the environmental representation might restrict the options available for robot position representation. Three fundamental relationships must be studied before choosing a particular map representation [41]:

a) The precision of the map must appropriately match the precision with which the robot needs to achieve its goals.
b) The precision of the map and the type of features represented must match the precision and data types returned by the robot's sensors.
c) The complexity of the map representation has direct impact on the computational complexity of reasoning about mapping, localization, and navigation.

In SLAM, there are two common representations: the geometric mapping and the topological mapping. A geometric map represents objects according to their absolute geometric relationships by capturing only aspects of object geometry that are relevant to localization. This level of simplification reduces memory usage on mapping. However, these maps derived from a sensor must be matched against past sensed landmarks in global coordinates, which offers great difficulties due to the robot's position error. The simplest way to represent a geometric map is the occupancy grid-map.

A. Occupancy Grid Map

Occupancy grid maps are spatial representations of robot environments. The method of using this type of map divides whole areas as the regular small grids and the rate which each grid is occupied is represented in probability value. Each cell may also have a counter, whereby the value 0 indicates that the cell has not been "hit" by any ranging measurements and, therefore, it is likely to be a free space. As the number of ranging strikes increases, the cell's value is incremented and, above a certain threshold, the cell is deemed to be an obstacle, as shown in Fig. 3. Once the map is acquired, they enable various key functions necessary for mobile robot navigation, such as localization, path planning, collision avoidance, and people finding [42].

The first of such map representations was the Certainty Grid developed by Moravec and Elfes [43]. In the Certainty Grid approach, the sensor readings are placed into the grid by using probability profiles that describe the algorithm's certainty about the existence of objects at individual grid cells. Borenstein and Koren [44] refined the method with the Histogram Grid, which derives a pseudo-probability distribution out of the motion of the robot.

In order to build a consistent map of the environment, a reliable localization is required. The inherent error from using only odometry data will result in an unsatisfying map. Vu et. al. tackled this problem by implementing particle filter in the localization of the vehicle in the occupancy grid map [45]. They introduced a new fast implementation of incremental scan matching method that can work reliably in dynamic outdoor environments.

Grid-based approaches offer discretized renditions of unstructured free spaces which can be used to localize a robot;

however the high resolution required for accurate representations demands large memory to store and high computation time to maintain.

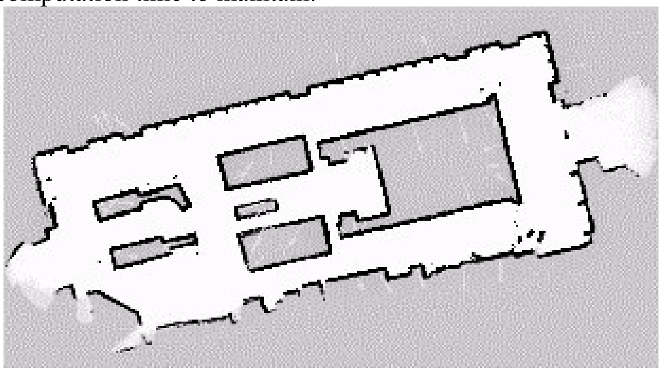

Fig. 3. Example of an occupancy grid map representation. [41]

Furthermore, any fixed decomposition method such as this imposes an initial geometric grid on the map, regardless of the environmental details. This can be inappropriate in cases where geometry is not the most salient feature of the environment.

B. *Topological Map*

By contrast, the topological approach is based on recording the geometric relationships between observed features rather than their absolute position with respect to an arbitrary coordinate frame of reference [46,47]. The resulting presentation takes the form of a graph where the nodes represent the observed features and the edges represent the relationships between the features.. Unlike geometric maps, topological maps can be built and maintained without estimates for the position of the robot. This means that the errors in this representation will be independent of other errors in the estimates of the robot position [48].

Information Filters are commonly used to build this kind of maps [49]. Kuipers and Byun [50] developed a three level hierarchy of control, topology, and geometry with which they simulated an exploration and mapping strategy. The control level determined distinctive places, the topological level tied these distinctive places together, and the geometric level built metric maps around this framework. Brad et. al., [51] combine the strengths of a topological map with those of a feature-based map. Topological techniques scale nicely to large spaces and higher dimensions, but cannot be used to position a robot at an arbitrary location. However, by using a topological map to decompose the space into regions, a feature-based map of moderate computational complexity could be built for arbitrary localization.

A mobile robot must satisfy two constraints in order to navigate based on a topological map. First, it must have a means for detecting its current position in terms of the nodes of the topological graph. Second, it must have a means for traveling between nodes using robot motion.

Recently, Gim et. al., [52] proposed algorithms integrating the grid and the topology map. The proposed scheme uses an occupancy grid map in representing the environment and then formulate topological information in a path finding algorithm. Simulations and experimental results from the work show that the performance of the proposed scheme to be faster and more stable. Choosing a map representation for a particular mobile robot requires the understanding of the sensors available on the mobile robot and its functional requirements.

VI. IMPLEMENTATIONS OF SLAM

Practical realization of probabilistic SLAM have become increasingly impressive in recent years, using the information obtained from the environment including the natural features, buildings, and even moving objects to address the SLAM problem.

A new strategy called Hierarchical SLAM, introduced by Estrada et. al., [53], allows accurate metric maps of large environments to be obtained in real time. Leonard et. al, [54] are working primarily with underwater robots and sonar sensors and have recently proposed submapping ideas, breaking a large area into smaller regions for more efficient map-building [55]. The philosophy of Constant Time SLAM, also proposed by Leonard and Newman [56], is to maintain the consistency, to look for global convergence and to develop an algorithm computationally more efficient using local submaps. Davison and Murray made the first application of active vision to real-time sequential map-building within a SLAM framework [20]. They showed that active visual sensing is ideally suited to the exploitation of sparse "landmark" information required in robot map-building. Since the complexity and variety of indoor environments, the ability of simultaneous localization and mapping for autonomous mobile robots restricted their applications. A novel approach, which is based on clustering algorithm, fuzzy logic and neural networks, is proposed by Dai et. al., [57] in solving the SLAM problem.

In order to improve the SLAM resolution, Zhang et. al. proposes a combination of the Gaussian Mixture Model (GMM) with Particle Filter (PF) and Unscented Kalman Filter (UKF) for the robot SLAM. From the simulation results shown in [58], the proposed methods work better than the FastSLAM and the UKF SLAM methods, especially in the case of dense landmark map.

On the other hand, Dual FastSLAM algorithm has been implemented and successfully tested in simulated and real experiments by Rodriguez-Losada et al [59]. Their simulations have shown a similar performance to FastSLAM 2.0 in cases of accurate external sensors, and the real experiments have successfully built maps of indoor environments, with a feature model based on the SPMap approach that adequately manages partial observations of geometric features with symmetries as the segments that are used to model walls.

Recently, the problem of Decentralized Simultaneous Localization and Mapping (DSLAM) has attracted new attentions. The main advantage of a decentralized data fusion system is the lack of dependency of the whole system on a central processing unit. Asadi and Bozorg [60] presented a decentralized information fusion algorithm for a land vehicle moving in an unknown environment. The algorithm is implemented using the field data obtained from an experiment, and the capabilities of the algorithm in the estimation of the vehicle position and the landmark positions are demonstrated. A decentralized architecture with applications in the global optimization of pedestrians' paths is presented in [61].

VII. APPLICATIONS

The utilization of robots in everyday human-activities has recently become a significant trend of research in robotics. There are several, commercially available household robots (iRobot, Anybots) that can perform basic household chores: from cleaning the room to assistance in serving food. However, all these complex tasks, are usually pre-programmed and cannot deal with the high degree of uncertainties usually associated with a human-populated environment. Therefore, intelligent technologies are required for autonomous execution of robots in the environments.

The Forestrix project studies forest and tree trunk measurement technologies, signal processing methods and algorithms for semiautomatic control of forest harvesters. Machine vision systems and scanning laser range finders have established themselves as standard equipment in mobile robotics. In this project, [62] a machine vision system is used to augment the map generated by the SLAM algorithm to get information about the surrounding forest. With the help of the laser scanner, the machine vision system divides camera images into sub images. Each sub image contains one dominant tree trunk. Different edge detection algorithms are used to extract the vertical edges of the dominant tree trunk. Using a calibrated camera and range information from the laser scanner, it should be possible to measure the actual diameter of the tree trunk with greater accuracy that is attainable with a laser scanner alone. The machine vision system should also be able to identify the tree type i.e. whether it is pine, spruce, birch, or other deciduous tree. This additional information should be stored in the tree map that is incrementally built by the SLAM algorithm.

Krys and Najjaran [63] describes a visual simultaneous localization and mapping (VSLAM) method for a pipe inspection robot that can serve as a carrier for nondestructive testing (NDT) sensors inside in-service water mains. Having a vision system onboard, the pipe inspection robot can perform localization and mapping and provide a 360º high-resolution global image of the internal surface of the pipe, using a sequence of images acquired by one or more digital cameras.

In surgery, the increasing use of Minimally Invasive Surgery (MIS) is motivated by the benefit of improved therapeutic outcome combined with reduced patient trauma and hospitalization. The technique is increasingly being used to perform procedures that are otherwise prohibited by the confines of the operating environment. Mountney et. al. [64] have developed a robust technique for building a repeatable long term 3D map of the scene whilst recovering the camera movement based on SLAM to estimate the movement of the stereolaparoscope during MIS and build a map of the anatomical structure. The method has been validated with a simulated data set using real MIS textures, as well as in vivo MIS video sequences. The results indicate the strength of the proposed algorithm under the complex reflectance properties of the scene and the potential for real-time application for integrating with the existing MIS hardware.

Perceiving or understanding the environment surrounding of a vehicle is a very important step in driving assistant systems or autonomous vehicles. The task involves both SLAM and detection and tracking of moving objects (DATMO). While SLAM provides the vehicle with a map of static parts of the environment as well as its location in the map, DATMO allows the vehicle being aware of dynamic entities around, tracking them and predicting their future behaviors. It is believed that if we are able to accomplish both SLAM and DATMO in real time, we can detect every critical situations to warn the driver in advance and this will certainly improve driving safety and can prevent traffic accidents [45].

In an urban search and rescue scenario, detecting the locations of survivors and then recovering them from a collapsed building is one of the biggest challenges faced by emergency response personnel. The environment can be unstable and difficult to negotiate while survivors trapped need to be rescued within a short time frame. SLAM technique used by robots and autonomous vehicles to assist human rescuers in such situations is one of the areas where robotics research can be of great benefit to humanity. Basically, the robots have to solve autonomously in real-time the problem of SLAM. Kleiner et. al. [65] proposes a novel method for real-time exploration and SLAM based on RFID tags that are autonomously distributed in the environment, which allows the computationally efficient construction of a map within harsh environments encountered after a disaster, and coordinated exploration of a team of robots.

VIII. POSSIBLE DIRECTIONS OF FUTURE RESEARCH

Currently, the assumption behind the map representations is that all objects on the map are effectively static. In general, these map representations should have explicit facilities for identifying and distinguishing between permanent obstacles (e.g., walls, doorways, etc.) and dynamic obstacles (e.g., humans, shipping packages, etc.). This is particularly true when one considers the home environment with which domestic robots will someday need to contend. However, neither the occupancy grid representation nor a topological approach is actively recognizing and representing moving objects as distinct from both sensor error and permanent map features.

Another open challenge involves the interpretations of open spaces. Existing localization techniques generally depend on local measures such as range, thereby demanding environments that are somewhat densely filled with objects that the sensors can detect and measure. Wide-open spaces such as parking lots, fields of grass, and indoor atriums such as those found in convention centers pose a difficulty for such systems because of their relative sparseness.

Another possible direction for future research in this field would be sensor fusion. A variety of measurement types are possible using off-the-shelf robot sensors, including heat, range, acoustic and light-based reflectivity, color, texture, friction, and so on. Sensor fusion is a research topic closely related to map representation. Just as a map must embody an environment in sufficient detail for a robot to perform localization and reasoning, sensor fusion demands a representation of the world that is sufficiently general and expressive that a variety of sensor types can have their data correlated appropriately, strengthening the resulting percepts well beyond that of any individual sensor's readings.

IX. CONCLUSION

In this paper, we have provided a comprehensive introduction to the SLAM problem and its relevant research referenced extensively. The concept of autonomy of mobile robots encompasses many areas of knowledge, methods, and ultimately algorithms designed for trajectory control, obstacle avoidance, localization, map building, and so forth. Practically, the aims of the SLAM in a real-world environment is to obtain faster processing speed, more precise predictable results, and better system approximation and consistency. Clearly, the robot's sensors and effectors play an important role in all forms of SLAM. It is because of the inaccuracy and incompleteness of these sensors and effectors that SLAM poses difficult challenges and remained an unsolved problem. At present, we have robust methods for mapping environments that are static, structured, and of limited size. Mapping unstructured, dynamic, or large scale environments remains largely an open research problem.

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