

ARTIFICIAL INTELLIGENCE FOR LONG-TERM ROBOT AUTONOMY: A SURVEY

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DOI: <https://www.doi.org/10.58257/IJPREMS37852>

ABSTRACT

Autonomous systems will be crucial for several applications in a variety of fields, such as field, road, marine, aviation, space, and service robotics. They will help us with our everyday activities and carry out tedious, hazardous, and filthy jobs.

However, there are numerous obstacles in allowing robotic systems to operate independently for weeks, months, or years in challenging, real-world situations. Some of them, such as navigation and mapping, sensing, knowledge representation and reasoning, planning, interaction, and learning, have been studied by subdisciplines of artificial intelligence (AI). The many subfields have produced methods that, when reincorporated into an autonomous system, can help robots function well in challenging, extended situations. In this letter, we examine and talk about AI methods as "enablers" for long-term robot autonomy, present advancements.

1. INTRODUCTION

Over the past ten years, ROBOT technology has advanced significantly. As a result, autonomous robot systems may now function for longer periods of time— weeks, months, or years—and in increasingly complicated situations. The problem of long-term autonomy (LTA) becomes one of resilience, or allowing the robot to continue operating for as long as possible, when a fully mod- elled robot is placed in a completely known, static environment. In the absence of these simplified presumptions, autonomous robots encounter several interconnected difficulties. We use two dimensions to roughly charac- terize these difficulties. The first one talks about the application requirements, such as the environment, tasks to be completed, and the robot platform (hardware and software).

The manuscript was approved on July 11, 2018, after being received on February 24, 2018. Publication date: July 27, 2018; cur- rent version date: August 9, 2018. Associate Editor G. Sibley and Editor D. suggested that this letter be published.

Lee, after considering the reviewers' remarks. A portion of this work was funded by EU project No. 732737 (ILIAD), EPSRC under Grants EP/M019918/1 and EP/R02572X/1 (NCNR), and CZ projects 17-27006Y and CZ.02.1.01/0.0/0.0/16_019/0000765. L.

Kunze, N. Hawes, T. Duckett, and M. Hanheide are the editors of the IEEE Robotics and Automation Letters Special Issue on AI for Long-Term Autonomy, which includes this study. (Lars Kunze is the correspondent.)

The Oxford Robotics Institute, Department of Engineering Science, University of Oxford, Oxford, employs L. Kunze and N. Hawes. explains these elements' long-term character, such as if and how they evolve over time, whether their long-term characteristics (structured vs. unstructured) can be precisely described beforehand, and their degree of observability. For instance, the environment will alter during the system's lifespan in many long-term applications. These modifications may be short-term (e.g., objects moving into the robot's range of vision), medium-term (e.g., furniture shifting between rooms, parked automobiles shifting locations on roadways), or long-term (e.g., plant growth, seasonal variations, surface wear). Furthermore, new objects may develop or aspects of the environment may not be completely understood prior to deployment they become accessible.

In this letter, we examine methods and systems that use AI techniques to handle the difficulties of LTA. We concentrate on AI methods that are employed by robot systems that are placed in real-world settings for extended periods of time (Sec. II) as well as methods that are well suited to the requirements of LTA systems in the future but have not been proven to work in long-term scenarios (Sec. III). We also go at upcoming AI potential and problems in LTA (Sec. IV).

We intentionally leave out other applications where robots work for extended periods of time in comparatively static, well-known environments by concentrating on the aforementioned difficulties. This specifically means that we don't include intra-logistics or manufacturing systems as they exist now. Most deployed robot systems have shown notable durability in both situations, however this is usually accomplished by creating completely understood ecosystems with

dynamics that are mostly controlled by autonomous systems. This reduces the LTA-specific issues (such as environmental dynamics, lack of structure, and open-endedness) observed in other domains, but it does not do away with the necessity of AI techniques (such as long-term localization [1] and planning [2] for warehouse AGVs). Due to the lengthy history of autonomous systems research, there are already specific problems and studies pertaining to LTA. For instance, AI techniques in integrated robot systems are covered in [3], [4]. Existing collections in perception address visual place recognition [8], calibration [7], and localization and mapping in dynamic contexts [5], [6]. This survey, however, is the first to concentrate exclusively on AI methods for enabling long-term robot autonomy.

Space, marine, aviation, field, road, and service are just a few of the domains where long-term autonomous robots have been deployed. An overview of these domains is given in Tab. I. chosen systems that are characterized by shared characteristics. We use the terminology of [4] in this survey and categorize domains according to application properties, including partial observability, cost & criticality, interaction & cooperation, task diversity, environment variability, semantics, dynamics, and degree of autonomy. Three levels (low, medium, and high) are used to qualitatively evaluate every characteristic, much like in [4]. For a thorough explanation of the features, please refer to the previously stated publication. The evaluation of deployed robot systems is the main objective of this effort. In order to achieve this, we evaluate them according to the length of time they have been in use (days, months, or years) and the degree of integration between various AI domains (not, partially, or fully integrated). Systems that don't use AI approaches from a certain field are distinguished by the three qualitative levels of integration; those that use them only partially, but not for LTA; and fully integrated systems that use them for LTA.

Space: Autonomous systems are necessary for efficient extraterrestrial exploration because of severe communication delays and restricted prior access. It was just the 5,000th day that NASA's Opportunity rover has been on the surface of Mars. A mixed-initiative task planner and an autonomous navigation system give it its independence. The planner (MAPGEN, [9]) automatically generates a daily mission program, which is subsequently adjusted by scientists on Earth. Stereo cameras are used by the navigation system to create 3D models for path planning and terrain traversability [10]. The use of LTA in satellite operations has also increased; for example, the Intelligent Payload Experiment (IPEX) showed more than a year of autonomous information collection with the use of image processing and planning technologies [11].

Marine: The needs and advantages of autonomy in marine and space robots are similar because of the limitations of communication across water and the challenges of completely mapping deployment sites. Long flights involving thousands of kilometers and hundreds of days are common for autonomous wave gliders (e.g., 7,400 km in 221 days [14]). Gliders are low-powered, comparatively simple robots. For days of autonomous operation, such as for ice navigation, more potent technologies have been put into place [12]. Field tests [13] and controlled environments aimed at LTA [28] have demonstrated the advantages of AI planning. Air: Energy is the primary component that hinders the long-term operation of aerial systems. According to the authors of [15], the UAV must plan its course in accordance with local and global weather conditions, wind fields, and thermal updrafts in order to achieve permanent autonomous flying. The capacity to pause flight in order to recharge, as demonstrated by the lake monitoring system in [29], offers an alternative to everlasting flight. Field: In a variety of industries, including forestry, agriculture, mining, construction, etc., field robotics works in dynamic, unstructured situations. These domains are described by Bechar and Vigneault [30] based on the degree of structure found in the surroundings and the robot-relevant objects. The vast majority of field robots in use today rely on GPS-based auto-steer systems that follow preset routes with little assistance from artificial intelligence and repeat to allow for reliable field navigation. These methods include driving systems down a training path, which they then independently retrace [31]. According to Krajnik et al. [17], their teach-and-repeat approach is resistant to variations in appearance throughout the year. According to Paton et al. [16], integrating several experience-based representations [39] produces a system that can navigate autonomously for an extended period of time even when the appearance of the surroundings drastically changes. Road: Using a vision-based driving system, the PANS platform [21] became one of the first autonomous cars to travel a considerable distance (6,000 miles, 98.2% autonomous driving) on public roads over a six-month period. It learned a mapping between road photos and suitable vehicle turn radiuses using a neural network. Service: We define service robots as working robots. For in conjunction with, people in settings that aren't specifically designed to accommodate them. Service robots have to deal with open worlds because of humans, dynamic surroundings because of people moving, day-night shifts, etc., and shifting task needs. Numerous research projects have implemented mobile robot systems with LTA capabilities in offices (Willow Garage [25], CoBot [27], and STRANDS [26]), museums (the groundbreaking Rhino [23] and Minerva [24]), retail establishments [32], and care settings (STRANDS [33] and Tangy [34]). The majority of these robots were around unsuspecting users and were in operation for at least a few weeks. The majority of these systems were set up periodically in the same setting (daily, for example). Additionally, the Willow Garage and STRANDS systems tried

continuous autonomous operation, controlling up to 28 and 13 days of uninterrupted operation, respectively. The current generation of autonomous service robots functioning in human-populated areas is the result of these research systems. Savioke's robot hotel butlers, Knightscope's security robots, and Bossanova's stock-checking robots in Walmart shops are a few examples. In conclusion, the only AI domains that were present in every system surveyed were Navigation & Mapping and Perception. Given that they provide robots relatively basic capabilities, this is hardly surprising. The majority of systems supported both planning and KR & Reasoning. However, we hypothesize that the dearth of semantics in the space and marine domains limits progress on KR & Reasoning. Additionally, it's noteworthy that systems only Most domains (apart from the service domain) only partially (if at all) facilitate interaction and learning. Despite being thoroughly studied overall, these topics haven't received much attention in long-term scenarios. As we note in Sec. IV, we therefore think that there are a lot of unresolved issues and research prospects for both fields (and their interaction).

LTA systems inherently pose an integration issue across all domains, especially when disparate AI capabilities must cooperate. There has been a growing movement in recent years to (re-)integrate AI approaches into robotics. Robots usually combine object and/or human navigation, localization, and navigation to handle difficult tasks and environments. perception, along with scheduling and/or task planning. Even though system-level integration of AI techniques is a crucial component of all research initiatives, there is currently no standard solution and limited study on how to integrate modules from various AI domains. Researchers can use standard techniques to combine their software components and other components in an organized manner thanks to robotic software development [35] and robotic middleware initiatives like the Robot Operating System (ROS) [36]. On top of these middlewares, some frameworks incorporate specific AI techniques for planning and execution (ROSPlan [37]), knowledge-enabled perception (RoboSherlock [38]), and long- term navigation planning and task scheduling (STRANDS [26]). These frameworks generally facilitate the usage and integration of various AI techniques. This section explains how various AI domains can facilitate autonomous robot systems to function for lengthy periods of time in real-world settings. This covers vision, knowledge representation and reasoning, navigation and mapping, preparation, communication, and education. A. Mapping and Navigation For autonomous robots to move with purpose, navigation is a necessary skill. As previously mentioned in Sec. II, one method employs visual "teach and repeat" to enable reliable navigation in field settings. In this method, the robot learns a map while being driven along a training path and then repeats the route on its own [16], [17], and [31]. More than 140 kilometers of autonomous driving, including nighttime driving, were shown in recent study [39] with an autonomy rate of 99.6%. In the last three decades, there has been a great deal of interest in autonomous robot learning of environmental models, particularly the simultaneous localization and mapping (SLAM) challenge [6]. The majority of methods, however, make the assumption that the world is static and fail to take into account the long-term updating of robot maps to account for changes in the surroundings. Here, we provide a brief overview of a number of complementary approaches that, when combined with long- term data sets for respective experiments, allow for long-term mapping and localization in dynamic situations. Multiple representations: Long-running robots must decide what to remember and what to forget because environment mapping is an ongoing process. It is dangerous to remove data from a map, though, because a change that is seen might just be momentary, and the environment could still return to its prior state. Thus, one strategy is to have several representations of the environment [8], after which the most pertinent model is chosen for planning and localization at the moment. Using strong statistics and several local maps at various timescales, early work. [40] created dynamic maps that accommodate changes. The localization process uses the map that best describes the available sensor data. While the longer-term maps are modified offline, the short-term maps are updated online.view-based depictions of mapped places, eliminating views that are no longer relevant, hence reducing the size of the entire map. Likewise, Churchill and Newman [43] suggest incorporating comparable observations at the same spatial locations into "experiences" that arethen connected to a specific location. They choose the experience for localization based on how well it corresponds with the robot' visual input. Keeping the data from every mapping session and combining them offline into a single, high-fidelity representation is an alternate strategy [44].Representations of mapped places depending on views, while removing views that are no longer relevant, hence reducing the size of the entire map. Churchill and Newman [43] also suggest incorporating comparable observations at the same spatial places into "experiences" that are thereafter linked to a specific location. They choose the experience that most closely resembles the robot's visual input for localization. A different strategy is to preserve the information from every mapping session and combine it offline into a single, high- fidelity representation [44]. understanding about dynamics: Another tactic is to model the dynamics, whereas the aforementioned methods focus mostly on understanding the scene's enduring features. Tipaldi et al. [53] demonstrated how their method increases localization robustness in a parking lot setting by using dynamic occupancy grids, which model each cell's occupancy as a two-state Markov process. Kucner et al. [54] model common motion

patterns in dynamic situations by learning the conditional probabilities of neighboring cells in an occupancy grid. In order to improve localization and navigation in human-populated environments, Krajník et al. [55] suggested using Fourier analysis to represent rhythmic or periodic processes in the environment. They demonstrated that the resulting spectrum models derived from long-term experience allow prediction of future environment states. Prominent uses of long-term 4D reconstruction method for crop monitoring over time [57] and an autonomous surface vessel conducting a 14-month visual survey of natural surroundings [56] are two examples of mapping. The latter includes optimization of the entire 4D reconstruction, data association to identify correlations between crop rows and sessions, and a 3D SLAM pipeline. Lastly, by removing the finer features of metric and feature-based representations, related work on topological and semantic mapping may improve long-term robustness to change even more. However, a thorough analysis is outside the purview of this letter. Given the continued deployment of long-running systems in practice, current trends indicate that future work on long-term navigation and mapping will involve more application-specific advances across all disciplines.

B. Observation Autonomous robots require general perception routines for object detection and scene comprehension in addition to perception algorithms for mapping and navigation. Early methods of mapping dynamic settings were, in fact, object-centric. These techniques either leverage moving landmarks for self-localization [59] or detect moving objects and eliminate them from the maps [58]. Long-term observations are necessary to identify dynamic objects because not all of them move at the time of mapping. In order to overcome this difficulty, Ambrus et al. [60] analyzed many 3D point clouds of the same scene that were captured over a number of weeks in order to distinguish and isolate mobile items while also improving the static environment structure. A method for long-term localization based on explicit object reasoning was put forth by Biswas & Veloso [61]. Groups such as unmapped dynamic objects, unmapped static objects, and mapped objects. In order to maintain computational tractability, Bore et al. [62] assume a closed world for detecting and localizing items in vast spaces, where objects may move between robot observations. Other methods, such as querying potential category labels from semantic knowledge on the web utilizing spatial context information, allow for open-ended learning of new item categories during long-term operation. A lifelong learning framework in which a human user can instruct a robot to gather domain-relevant data for training classifiers of household objects [64] and an embodied system for open-ended learning and manipulation of new object categories based on human-robot interaction [63] are examples of recent work. Techniques to enhance future service robots' perception of humans over time would also be advantageous, such as incorporating long-term experience in tracking-learning-detection [65] and tracking-learning-classification [66] approaches, as well as learning people's long-term activity patterns [67]. Robots would therefore be able to adjust to and move more in unison with the anticipated human flow. Algorithms for person re-identification at various temporal scales (very short term, same day, different day) are also necessary for long-term applications involving interaction with unique individuals. Depending on how persistent the supporting cues are (e.g., place at the dinner table, attire, size/stature, hair color, facial features), various assumptions can be made for these situations. Recent research combines multi-target multi-camera tracking with human re-identification [68], but autonomous robots still face the issue of adapting person-specific appearance models over extended periods of time. There are clear analogies to other related problems, such as identifying human activity, where performance can be gradually improved by utilizing long-term experience [69]. Generally speaking, the majority of earlier perception research simply takes into account the first training stage before deploying.

C. Reasoning and Knowledge Representation Knowledge representation (KR) is strongly related to many other disciplines of artificial intelligence (AI) and focuses on describing the world, especially in domains with rich semantics (see Tab. I). Including learning, planning, and perception. Important facets of representations in relation to perception and navigation were covered in the earlier sections. Since inference and decision-making are closely related to how knowledge is represented, KR generally goes hand in hand with reasoning. In order to represent and reason about many parts of the world, especially as they change over time, long-term autonomous robot systems deployed in real-world contexts need KR and reasoning capabilities. Thus, in long-term scenarios, AI domains including spatiotemporal reasoning, non-monotonic reasoning, and belief revision are crucial. Models that infer the locations of entities in space and time were examined in a number of studies. An object-based semantic world model for long-term transformation was put forth by Mason et al. [70]. Identification in dynamic settings, and [71] modeled an object's persistence throughout time. Similar to this, frequency-based spatiotemporal models for determining people's whereabouts were put forth by Krajník et al. [72]. In long-term scenarios, such spatiotemporal data is crucial because it can provide AI planners with knowledge about non-stationary costs and/or benefits (see Sec. III-D). A novel lifetime information-driven method for spatiotemporal exploration that gradually completes and improves environment maps was introduced by Santos et al. [73]. The ability of robots to access and learn from their own experience is crucial for LTA. A KR infrastructure called OPEN-EASE [74] enables semantic accessibility of experience data from robot and human manipulation experiences. Users

are able to retrieve experiences and ask questions about the robot's perceptions, reasoning, and actions. According to Balint-Benczedi et al. [75], a more specialized framework for long-term manipulation tasks that stores and retrieves perceptual memories. In a similar vein, [76] suggest a framework for long-term knowledge acquisition that makes use of contextual data in a robot design influenced by memory. For example, in a manipulation task, the framework enables robots to memorize and retrieve their views. Novelty and anomaly detection are critical to overcoming the difficulties of open environments. In order to do this, [77] put out a paradigm for anomaly reasoning that covers the identification and interpretation of both known and unknown things showing up in unexpected settings. Because it can initiate learning in LTA systems, this component of KR and reasoning is closely related to studies in adaptation and learning (Sec. III-F). D. Planning Artificial intelligence (AI) planning and scheduling technologies, which identify the steps required to complete a task, are frequently used to modify a robot's behavior online to take task or environment dynamics into account [4]. Almost all LTA systems have planning systems installed. Planning techniques, for instance, were employed to create daily job lists and the corresponding action sequences for the Opportunity rover [9], as well as the service robots STRANDS [26], CoBot [78], and Tangy [34], which enable these robots to modify their behavior in response to human demands. While logistics systems employed planning to allow for a large number of robots to handle a variety of client requests [2], AUVs used planning to deal with shifting environmental conditions and resources [13]. The capacity of different planning techniques to capture important aspects of a system's long-term experience varies. The systems listed above differ in whether or not they simulate how a robot's actions affect time or resources.

2. CONCLUSION

Although they are outside the purview of this letter, in addition to these technological difficulties, the realization of LTA systems raises ethical, social, and legal concerns. Overall, we are certain that AI techniques can give LTA systems many of the features required to get beyond these obstacles. By utilizing long-term experience, AI techniques may really aid in the resolution of some of the most challenging unresolved robotics issues, such as perception-based mobile manipulation in real-world environments, rather than just prolonging the lifespan of already available AI-enabled robots. But even with recent advancements, we acknowledge that there are still a lot of fascinating unsolved problems.

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