

# Introduction to the Special Issue on AI for Long-Term Autonomy

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## I. INTRODUCTION

Autonomous systems have a long history in the fields of Artificial Intelligence (AI) and Robotics. However, only through recent advances in technology has it been possible to create autonomous systems capable of operating in long-term, real-world scenarios. Examples include autonomous robots that operate outdoors on land, in air, water, and space; and indoors in offices, care homes, and factories. Designing, developing, and maintaining intelligent autonomous systems that operate in real-world environments over long periods of time, i.e. weeks, months, or years, poses many challenges. This special issue focuses on such challenges and on ways to overcome them using methods from AI.

Long-term autonomy can be viewed as both a *challenge* and an *opportunity*. The challenge of long-term autonomy requires system designers to ensure that an autonomous system can continue operating successfully according to its real-world application demands in unstructured and semi-structured environments. This means addressing issues related to hardware and software robustness (e.g., gluing in screws and profiling for memory leaks), as well as ensuring that all modules and functions of the system can deal with the variation in the environment and tasks that is expected to occur over its operating time. Early research in long-term autonomy for mobile robots focussed extensively on the problem of coping with environment variation, e.g., performing visual localisation over seasonal changes, or SLAM in a dynamic environment. Once such challenges are overcome, the long-term operation of an autonomous system provides the opportunity to specialise that system to its tasks and operating environment, potentially improving both its general robustness and more specific task performance. This specialisation may come through the use of extensive system logs to detect and fix bugs, or through automatic online adaptation via machine learning. There is also the opportunity to aid development through the use of logs to create tests and simulations which are representative of a specific system deployment.

A great many research fields have the potential to contribute to enabling and improving long-term operation of autonomous robots. For example, formal methods can be used to verify robot software or control policies to ensure safe long-term operation, and novel locomotion methods can be used to minimise a robot's long-term energy usage. However, we chose to focus on AI techniques for long-term

autonomy since AI provides a wide range of algorithmic approaches for addressing both the challenge of online long-term variation in task and environment (e.g. through task planning or probabilistic inference), and for the opportunity of online adaptation through experience (via machine learning). There are also a variety of AI techniques which have yet to be extensively applied in long-term settings, and we therefore see long-term autonomy as a motivating challenge for our community in the years ahead. This challenge has huge societal and industrial relevance as autonomous systems enter our lives in ever increasing numbers.

## II. GUIDE TO THE SPECIAL ISSUE

The overview of AI for long-term autonomy presented above is greatly expanded in the survey paper included in this special issue [1]. The survey approaches the topic from two complementary angles. It starts by surveying autonomous robot systems that have been fielded in uncontrolled environments for extended periods, grouping these systems across application domains such as space, marine, service and road. It then surveys the AI techniques which cut across these systems and identifies trends in the approaches used to provide long-term behaviour in fielded systems. It concludes by identifying future challenges and opportunities around AI for long-term autonomy. The survey groups AI techniques under research areas including Navigation & Mapping; Perception; Knowledge Representation & Reasoning; Planning; Interaction; and Learning. Three of these areas in particular are represented by the other papers in the Special Issue, described as follows, while the other areas present excellent opportunities for novel future research in AI for long-term autonomy.

### A. Interaction

Human-robot interaction research for autonomous long-lived systems has two facets: the modelling and analysis of interaction over long durations; and the support of long-term autonomy through interactive learning.

An example of the latter is the work by Del Duchetto et al. [2], who employ Gaussian Processes in order to interactively learn local navigation recovery behaviours for mobile robots. Using a long-term dataset, they highlight that navigation failures are predictably localised in space-time, and propose a solution that can exploit rare interactive teach-in opportunities from situations where the robot was helped by human bystanders.

Herrero et al. [3] provide a comprehensive analysis of the user base of an autonomous system, which was deployed for long-term operation in a care home, hence studying

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long-term interaction of an autonomous robotic system. The core contributions of the paper are a processing pipeline to automatically estimate demographics (age, gender) of interacting users, and a model to discriminate between passive interactions (bystanders observing the mobile robot), and active interactions (users directly interacting with the robot). Their work facilitates user analysis of robots deployed “in the wild”, i.e. without experimenters on site, in long-term settings.

### B. Perception

Pre-trained detectors and classifiers are usually used to allow a robot to perceive the objects in its environment. In a long-term setting it is not typically possible to predict in advance the complete set of objects that a robot needs to perceive, or the contexts in which they may occur.

Chaudhary et al. [4] address part of this problem by developing a technique to segment generic hand-held objects from RGB-D input. These segmentations can then be used during long-term operation as input into an online object learning approach. The paper presents a methodology based on a deep comparison and segmentation network which significantly outperforms state-of-the-art object segmentation methods from literature.

### C. Navigation & Mapping

Maps are needed for wayfinding and other spatial reasoning tasks. In a long-term autonomy setting, maps must support these capabilities under the variation of the environment over the lifetime of the system. The contributed papers in this special issue address some of the core problems in long-term mapping and navigation by mobile robots, including long-term visual place recognition [5], [6], SLAM [7], and semantic mapping [8].

Han et al. [5] introduce a novel representation for visual place recognition that simultaneously integrates semantic landmarks and holistic information to achieve long-term operation. Evaluations on public benchmarks, including the Nordland and CMU-VL datasets, demonstrate the ability to recognise places in long-term scenarios, while outperforming state-of-the-art approaches for visual recognition.

Chen et al. [6] propose a visual attention model for place recognition, which learns to automatically focus on regions that are most discriminative in defining a place, using context information extracted from a deep neural network. Evaluation against state-of-the-art approaches, including FABMap and SeqSLAM, on several benchmarking datasets demonstrated superior performance in place recognition against strong viewpoint and condition variations.

Bescos et al. [7] present a dynamic SLAM algorithm, DynaSLAM, for handling dynamic objects in RGB-D, stereo and monocular SLAM, by adding a new front-end for motion segmentation to the existing ORBSLAM2 system. Evaluations on the TUM Dynamic Objects and KITTI datasets show that DynaSLAM outperforms the accuracy of standard visual SLAM baselines in highly dynamic scenarios.

Sun et al. [8] propose an approach for long-term semantic mapping, using a deep-learning approach to fuse the semantic features from 3D lidar data, where the dynamic state of each cell in a 3D OctoMap is modelled by a recurrent neural network. Evaluations on the ETH Parking-Lot dataset demonstrate the ability to learn the semantic state transitions while outperforming conventional Bayesian updates in long-term scenarios.

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