A 3D Simulation Environment with Real Dynamics: A Tool for Benchmarking Mobile Robot Performance in Long-term Deployments

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***Abstract*— This paper describes a method to compare and evaluate mobile robot algorithms for long-term deployment in changing environments. Typically, the long-term performance of state estimation algorithms for mobile robots is evaluated using pre-recorded sensory datasets. However such datasets are not suitable for evaluating decision-making and control algorithms where the behaviour of the robot will be different in every trial. Simulation allows to overcome this issue and while it ensures repeatability of experiments, the development of 3D simulations for an extended period of time is a costly exercise.**

In our approach long-term datasets comprising high-level tracks of dynamic entities such as people and furniture are recorded by ambient sensors placed in a real environment. The high-level tracks are then used to parameterise a 3D simulation containing its own geometric models of the dynamic entities and the background scene. This simulation, which is based on actual human activities, can then be used to benchmark and validate algorithms for long-term operation of mobile robots.

***Index Terms*— mapping, spatio-temporal, long-term autonomy, benchmarking**

I. Introduction

In recent years, we have witnessed an increase in the deployment of robotic platforms in real-world applications such as search and rescue, security, and healthcare. Even though current technology has allowed us to successfully employ mobile robots in human-populated scenarios, their deployment is still a difficult process due to the many challenges caused by human activity. Unlike highly structured environments, such as factory assembly lines, these scenarios are under continuous change and in order to successfully perform its daily tasks, the robot must be able to adapt. Thus, the long-term deployment of such robotic platforms requires mapping, navigation and planning algorithms that are able to deal with the changes in the environment and allow the robot to perform tasks reliably even if unexpected events occur.

The development of environment representations that model world dynamics not only allows to predict the environment states, but also improves the robustness of robot localization and the efficiency of path planning. Some authors have developed approaches that can cope with dynamics without explicitly representing them [1], [2], [3], [4]. Other authors [5], [6] have focused on models that explicitly represent the environment changes and try to identify patterns. Additionally, methods that allow to actively build and maintain spatio-temporal representations are described in [7], [8]. The outcome of the aforementioned strategies is typically an environment representation that not only takes into account the spatial configuration of the environment but also the way the environment states change over time.

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The work has been supported by the EU ICT project 600623 'STRANDS'.

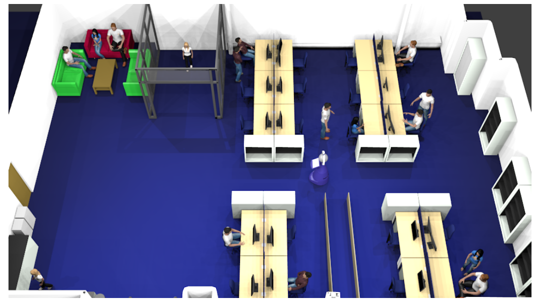

Fig. 1: Simulated environment for the L-CAS dataset.

The most common and accurate method to validate these models is to compare the model error with respect to ground truth. Spatial-only methods only require the ground truth to be built once due to the static world assumption. Replicating the same experimental conditions in order to compare these methods is relatively easy. However, for the long-term (spatio-temporal) case the ground truth must be built over time due to the changes in the environment that the robotic system should be able to deal with. Additionally, the comparison between spatio-temporal methods should be performed under the same conditions, which for real-world experiments can be difficult if not impossible. For example, to ensure the same conditions for all teams in the 2014 Kinect Autonomous Mobile Robot Navigation Contest[1], the dynamics introduced in the environment followed a strict sequence that precisely determined when, where and who should move around. In general, this is not a feasible method when evaluating the performance of autonomous systems over long periods of time. In most previous works on long-term autonomy for mobile robots, pre-recorded datasets of robot sensory data were used to evaluate state estimation algorithms such as mapping, self-localisation, people tracking and activity recognition. However, these pre-recorded datasets do not permit the experimenter to change the behaviour of the robot during the experiments. Simulation could be a very useful tool to allow long-term experiments to be repeated consistently in reasonable time. However building full 3D simulations for an extended period of time is itself a very costly exercise.

To address these issues we propose to record long-term datasets comprising high-level tracks of dynamic entities

[1]`http://www.iros2014.org/program/kinect-robot-navigation-contest`

such as people, furniture and other objects of interest, which may be captured with another sensor system, such as ambient person-presence sensors or hand-annotated images from an overhead fisheye camera in our experiments. Then these high-level tracks based on real sensor data are used to parameterise a full 3D simulation, which contains its own geometric models of the scene background and the dynamic entities. This allows to achieve a realistic simulation of object and behaviour spatio-temporal behaviour based on real-life dynamics rather than artificially generated dynamics, making the simulation a more accurate tool to compare different methods. The full 3D simulation can thus be used to benchmark mobile robot navigation algorithms which require decision-making and control of the robot, such as exploration or path planning, as well as state estimation algorithms such as 3D mapping and self-localisation.

II. System Description

The presented methodology consists of two main modules: 1) a simulation environment that provides the geometry of the environment and 2) a module that rearranges the dynamic entities in the environment over time according to what was captured by physical sensors installed in a real environment.

The simulation environment is based on MORSE[2], which is part of the STRANDS software package[3]. However, any other 3D simulation environment could be used, such as Gazebo. A 3D replica of the environment is first created, see Figure 1. This replica is based on the office plans and the current furniture arrangement. Several dynamic objects are then added such as chairs, laptops and humans.

The configuration module controls the simulation by maintaining a list of all entities and their positions in the environment, rearranging them in the environment depending on the logged events observed in the real world which are stored in a file. The aforementioned module uses the MORSE sockets middleware to send commands that reconfigure the simulation so that it follows the real dynamics.

III. The Datasets

The L-CAS dataset consists of a description of more than 20 objects and human positions over time. The data acquisition was performed using two fish-eye cameras installed on the ceiling, which took a snapshot of the environment every second. The dataset consists of a log file containing the positions of several dynamic object over time, which were obtained by manually annotating the successive snapshots taken by the cameras. The objects' positions were taken from videos recorded by two ceiling cameras.

The 'Aruba' [9] dataset is a year-long collection of measurements from 50 different sensors spread over an eight-room apartment occupied by a single, house-bound person who occasionally received visitors. All the monitored events present in the original dataset were processed in order to describe the people presence in the flat for every minute over 16 weeks. To complement this dataset, a 3D environment with the same structure as the 'CASAS' apartment was created by taking into account the building plans, see Fig. 2.

Fig. 2: Simulated environment for the 'Aruba' dataset.

IV. Conclusion and Future Work

This paper described a method that allows to benchmark spatio-temporal strategies in long-term deployments. Currently, the framework developed can use two different 3D environments, an apartment and an open office, which contain physical models of people and objects locations that change according to what was observed by sensors installed in both real-world environments.

The proposed solution was further used to validate a spatio-temporal exploration strategy that actively decides when and where the robot should make observations to build and maintain its environment model alongside its daily duties [7], [8]. The outcome of this exploration strategy is a 3D grid that models both the environment geometry and the typical patterns of state changes.

The L-CAS dataset is still under development in order to provide a better and more complete dataset that allows to simulate longer periods of time, as well as to increase the number of dynamic objects and achieve a more realistic simulation. For more details see `https://lcas.lincoln.ac.uk/owncloud/shared/datasets/`

[2] `https://www.openrobots.org/wiki/morse/`
[3] `http://strands.acin.tuwien.ac.at/software.html`

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