Lifelong Information-driven Exploration for Mobile Robots to Complete and Refine Spatio-Temporal Maps in Changing Environments

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Change is the essential process of all existence.

Spock, *Star Trek: The Original Series.*

Abstract

Recent improvements in the ability of mobile robots to operate safely in human populated environments have allowed their deployment in households, offices and public buildings, such as museums and hospitals. However, the structure of these environments is typically not known a priori, which requires the robots to build their own models of their operational environments. This process is commonly known as “exploration” in mobile robotics. Moreover, real-world environments tend to change over time, which means that to achieve long-term autonomous operation, robots must also update their environment models as a part of their daily routine. The assumption of a perpetually-changing world adds a temporal dimension to the exploration problem, making exploration a never-ending lifelong learning process. To the best of our knowledge, this process termed “lifelong exploration” has never been studied in detail before and forms the main topic of the work presented in this thesis. Efficient lifelong exploration requires a robot to choose the right locations and times at which to collect observations in order to improve its environment model.

To evaluate the ability of a robot to build and maintain its environment models, we need to be able to compare lifelong exploration strategies under repeatable experimental conditions. An evaluation methodology based on pre-recorded sensory datasets would not be suitable for this purpose, as this would not allow the robot to choose the location or time of its observations. Evaluating lifelong exploration requires the deterministic reproduction of environment changes, while preserving the robots ability to decide upon its own actions during the experiment. This thesis therefore contributes a new benchmarking methodology for lifelong exploration, which replicates the events occurring in real environments through physical simulations that reflect the environment changes gathered by ambient sensors over long periods of time. The established experimental benchmarks are based on long-term sensory datasets recorded in a smart home, with dynamics produced by a single person over a period of one year, and an office environment, with dynamics produced by a team of workers.

Building upon the aforementioned benchmarking methodology, the thesis investigates possible strategies for lifelong exploration. An experimental comparison of lifelong exploration strategies that combine various decision-making paradigms and spatio-temporal representations is presented. Moreover, a new approach to lifelong explorations is proposed that applies information-theoretic exploration techniques to environment representations that model the uncertainty of world states as probabilistic functions of time. The proposed method explicitly models the world dynamics and can predict the environment changes. The predictive ability is used to reason about the most informative locations to explore for a given time. A 16 week long experiment shows that the combination of dynamic environment representations with information-gain exploration principles allows to create and maintain up-to-date models of continuously changing environments, enabling efficient and self-improving long-term operation of mobile service robots.

The final part of the thesis considers the problem of acquiring and maintaining dense 3D models of dynamic environments during long-term operation, building on the work presented in the earlier chapters. The term “4D mapping” is used to indicate 3D mapping by mobile robots over extended periods of time. A new approach to lifelong 4D mapping and exploration is presented, which was deployed on a real robotic platform during long-term operation in real-world human-populated environments. The approach integrates sensory data captured by the robot at different times and locations into a global, metric

4D spatio-temporal model and then uses the model to decide where and when to perform the next round of observations. Finally, the deployment of the 4D exploration method in a real-world office scenario is described and evaluated. The one week long experiments show that the method enables reliable 4D mapping and persistent self-localisation of autonomous mobile robots, continually improving the robots maps to reflect the ever-changing world.

Keywords: Mobile Robotics, Service Robots, Long-term Autonomy, Spatio-temporal Mapping, Lifelong Exploration.

Declaration

The work in this Ph.D. thesis is based on research carried out at the Lincoln Centre for Autonomous Systems of the University of Lincoln in United Kingdom. No part of this thesis has been submitted elsewhere for any other degree or qualification and it is all my own work unless referenced to the contrary in the text.

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Acronyms

DFT Discrete Fourier Transform. 33, 38, 82, 83, 109, 110

FFT Fast Fourier Transform. 25, 63, 95, 110

FoV Field of View. 69

FreMEn Frequency Map Enhancement. 28, 29, 36, 39, 40, 44, 45, 58, 63, 66, 71, 72, 82–84, 95, 96, 110

FT Fourier Transform. 33, 34, 109, 110

GMM Gaussian Mixture Models. 60, 62, 63, 71

L-CAS Lincoln Centre for Autonomous Systems. VIII, 49, 52, 88

LM Long-term Memory. 60, 62

NBV Next Best View. 12, 16–18

PerGaM Periodic-GMM. 63

QSR Qualitative Spatial Representations. 31

ROS Robot Operating System. 30, 87

SaR Search and Rescue. 15, 18

SLAM Simultaneous Localisation and Mapping. 19, 26

SM Short-term Memory. 60

SO Spatio-Only. 87, 88, 91, 92

ST Spatio-Temporal. 88, 89, 91, 92

Nomenclature

$\mathcal{A}$	Frequency Spectrum of Observations
α	Components of Spectrum of Observations
$\mathcal{B}$	Corrective Spectrum
β	Components of Corrective Spectrum
$\mathcal{C}$	Corrected Frequency Spectrum
γ	Components of Corrected Spectrum
$\mathcal{D}$	Set of Candidate Observation Positions
$\mathcal{F}$	Fourier Transform
$\mathcal{G}$	Set of Observation Positions
ι	Minimal Entropy Corrective Constant
$\mathcal{L}$	Set of Locations to Visit
λ	Event Rate
μ	Mean Probability
$\mathcal{O}$	Set of Outliers
Ω	Set of Modelled Periodicities
ω	Angular Frequency
$\mathcal{P}$	Set of Prominent Spectral Coefficients
$\mathcal{S}$	Set of World States
σ	Variance
$\mathcal{T}$	Set of Time Intervals
ς	Saturation Function
$\oplus$	XOR Operator

1

Introduction

1.1 Context and Motivation

The ambition to achieve autonomous robotic systems that can assist humans in a diversity of tasks or even replace them in dirty, dangerous and dull situations has been driven by their successful application in different fields, including industrial and medical applications. The development of such systems is possible due to the advances in hardware technology that enabled computers to be more powerful, while using less energy, and the development of new sensors and their price reduction as a consequence of mass production. However, the hardware by itself is not enough to enable robots to operate in everyday scenarios and their deployment in human-populated environments is still an open challenge.

Like any other tool, robots were designed and developed with the purpose of assisting humans in their duties. These duties can range from simple manufacturing tasks to more complex security tasks, where the robot patrols a given environment, looking for anomalous events, or even assisting people with disabilities that have an impact on their cognitive and physical abilities. To make the above examples possible, a certain degree of reliability and robustness must be ensured. Thus, a key requirement for autonomous mobile service robots is the ability to operate over long-periods of time, which implies that the mobile robot should be able to deal with unexpected events, recover from failures and adapt to the different environment conditions.

The complex, uncertain, and unpredictable nature of human behaviour is one of the primary factors behind the particular challenges that a mobile service robot has to face during its long-term deployment. A service robot not only has to coexist and ensure the safety of humans, but also exchange information with them, perform its duties efficiently and adapt to the different events that might occur. Thus, the mobile robot needs to somehow deal with the incomplete knowledge of its operational environment, i.e., the environment uncertainty.

To address this uncertainty probabilistic mapping methods were developed that enabled the representation of the robot's operational environment through the knowledge extracted from noisy sensory measurements (Thrun et al. 2005). This model is typically not given a priori and a robot has to build it either autonomously or with the guidance of a human. Exploration strategies enable mobile robots to autonomously build a map of the environment by combining probabilistic mapping methods with planning techniques and allow the mobile robot to efficiently decide where to perform observations and ensure the model completion (Kuipers & Byun 1991).

Although the majority of mobile robotic systems rely on environment representations to perform their duties, a mobile robot does not necessarily require a map of its operational environment in order to perform tasks. For example, outdoor navigation tasks can be solved without explicitly modelling the environment by means of path following strategies (McManus et al. 2014). However, these strategies do not allow for global localisation and efficient path planning, which are desired features in any autonomous mobile service robot. Maps not only provide a representation of aspects of interest that describe the robot's operational environment, but they also play a key role in supporting the robot's tasks, providing the knowledge for efficient path planning and allowing a comprehensive visualisation for humans, which allows them to easily assign tasks to a specific location in the environment (Cadena et al. 2016). Additionally, maps allow to share information with other autonomous systems, decreasing the times and complexity of certain tasks.

Taking into account the above concepts, environment mapping is an essential part of the majority of autonomous mobile robot systems, especially when these systems are deployed in environments where assisting humans in their activities is the principal goal.

1.2 Mobile Robotic Exploration: Where to observe?

Figure 1.1 presents an overview of the typical approach to a fully integrated mobile robotic exploration system. It relies on three main components: mapping, localisation and planning. Their combination allows the robot to build the model of the environment by itself, use that model and the robot's sensors to identify where in the environment the robot is located and, finally, plan the best path and to avoid obstacles. Mobile robotic exploration strategies have to ensure that the resulting environment model is both complete and accurate (Kollar & Roy 2008) by planning which locations in the environment to observe next by considering the completeness of the current environment model.

Figure 1.1: *Based on the original by Makarenko et al. (2002), this diagram shows an overview of an integrated mobile robotic exploration system.*

While the above approach is suitable for acquiring the robot's initial map of the environment, it does not consider the problem of lifelong updating of the map in response to environment changes. As the robot's map becomes more and more out-of-date, the number of failures in the localisation and navigation systems will increase and might lead to a complete failure of the mobile robot system. These failures are typically related with the fact that most of the methods used in mobile robotics assume that the robot's operational environment does not change over time. Even though the static world assumption does not represent reality, it allows to reduce the complexity of the mapping and planning stages, assuming that the environment changes are not too severe to prevent continued operation. Probabilistic mapping methods can deal with conflicting measurements, but their approach is rooted in the idea that these variations are caused by inherent sensor noise rather than by structural environment change. Thus, these conflicting measurements are generally treated as outliers caused by unwanted noise and, consequently, the relevant knowledge that could enrich and improve the robot's maps and thus avoid such failures is ignored.

The increasing need to deploy robots in human-populated scenarios leads to new research questions like the ones studied in the field of long-term autonomy, which aims at developing new methods that enable mobile robots to operate over long periods of time. Furthermore, during its long-term operation, a mobile robot should be able to identify its failures, learn how to avoid and recover from them and, if necessary, request human-assistance. The field of long-term autonomy also covers questions such as optimising the robot's operation time by learning from the long-term experience, such as when to schedule maintenance tasks, when and how to perform the robot's daily duties, which objects to look for in order to fulfil its duties and, finally, how to operate in environments that change over time. To sum up, the goal is to achieve a self-improving autonomous robot that performs its tasks more and more efficiently over time by learning from its long-term experience.

1.3 Lifelong Exploration: *Where* and *When* to observe?

While the long-term deployment of mobile robots presents several challenges, it also offers the opportunities to observe novel situations that would otherwise be impossible to experience. Hence, the integration of these experiences in the robot's knowledge allows the mobile robot to gradually learn how to adapt or even avoid critical or difficult situations.

A mobile robot can experience different types of environment changes during its long-term operation, which can be classified as follows (Biber & Ducket 2009):

- fluctuations – e.g.people moving around;
- variations – e.g. events that exhibit certain patterns;
- structural changes – e.g. building alterations.

Whereas some of these changes might not affect the robot's performance, others might lead to the complete failure of the robot's navigation and localisation systems. Nevertheless, the categorisation of the different changes in the environment is only possible through the re-observation of the environment. However, the limits between each of these categories are not well defined, and thus there are no clear rules that allow a mobile robot to successfully interpret and adapt accordingly to the different environment changes. Instead of aiming at this categorisation, an analysis of the persistence and frequency of the environment changes allows to understand which changes should be learned (or kept in memory) and which ones should be discarded or even predicted.

Taking into account the previous concept, in order to achieve long-term autonomy, the environment models to be built by the mobile robot must take into account the different observations taken over the duration of the deployment, i.e., the different changes in the environment observed by the robot must be integrated in the environment model. The key contribution of this thesis is the development of methods that allow the robot to actively decide *where* and *when* to perform observations in order to understand the nature of the changes that occur in the robot's operational environment.

Figure 1.2 extends Figure 1.1 by adding the notion of time to the problem of integrated mobile robotic exploration. Mapping not only has to consider the environment structure, but also how the environment evolves over time leading to spatio-temporal mapping. In order to build a spatio-temporal map, all the observed environment states must be integrated into a model that allows to efficiently store all the observations, while enabling the robot to quickly make use of such knowledge and adapt to the environment changes. The robot's localisation system should be able to exploit the above spatio-temporal model in order to achieve life-long localisation and, finally, taking into account that the robot is able to reason over time using its spatio-temporal model, planning becomes a scheduling problem in which the robot reasons *where*, *how* and *when* to perform its tasks, balancing the different time constraints with the need to continue learning about its operational environment.

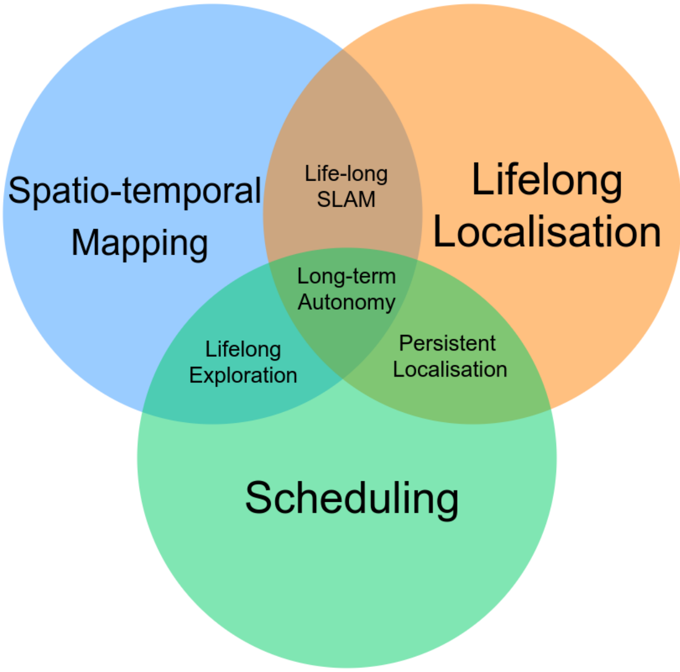


Figure 1.2: *Overview of the different modules required to achieve a long-term autonomy.*

Recently, some authors have exploited the conflicting measurements observed during long-term experiences in order to obtain information about the world dynamics and proposed representations that model the environment dynamics. These dynamic representations have shown their potential by improving mobile robot localisation in changing environments (Biber & Ducket 2009, Dayoub et al. 2011, Churchill & Newman 2013, Krajník et al. 2014a, Tipaldi et al. 2013, Neubert et al. 2015). Similarly to traditional robotic mapping, introduction of spatio-temporal mapping naturally requires novel techniques that allow to reason about how to efficiently build and maintain spatio-temporal maps during the robot's deployment by means of lifelong exploration.

This raises several questions regarding exploration of changing environments:

- How to evaluate and compare different lifelong exploration strategies that create, maintain and refine representations of changing environments?

- Which environment models should be used to represent the ever-changing world?

- How to drive the robot's attention to the right locations and times?
- Can such a system work in a real robot that has to perform other tasks?
- How does lifelong exploration improve the efficiency of robot operation?

Based on the above questions, this PhD thesis proposes an information-driven approach to lifelong exploration that integrates observations taken at different times and locations into a spatio-temporal environment representation which is then used to determine where and when to perform new observations, while being able to cope with the robot's daily duties. Thus, this thesis is going to focus on both mapping and environment representations and planning strategies for lifelong operation of mobile robots. While localisation is fundamental for any mobile robot, it is highly dependent on the quality of the robot's world model. In order to easily identify and understand the impact of the different lifelong strategies and representations on the ability to build and maintain world models, the robot's localisation is assumed to be perfectly accurate. This reduces the complexity of the overall mapping process and planning and enables a focused experimental validation.

1.4 Main Contributions

This section lists the novel contributions to the field of long-term autonomy for mobile robots, which are as follows:

- A memory efficient 3D environment model for changing environments is presented and described in Chapter 3. Experiments using a real-world dataset allowed to evaluate the compression performance as well as the ability to predict the environment's future states.
- Novel methodologies to benchmark and compare spatio-temporal environment representations as well as exploration strategies are presented in Chapter 4, which are fundamental to support the development of strategies for long-term autonomy.
- The concept of lifelong spatio-temporal exploration is presented in Chapter 5, extending the definition of spatial exploration by taking into account time and the fact that human-populated environments are continuously changing.

- A study using the aforementioned benchmarking tools is conducted in Chapter 5. Several spatio-temporal strategies and goal generation methods are compared under the same experimental conditions.

- The concept of spatio-temporal exploration is extended to 3D grids by extending the previous methods to a fully functional real-world system (Chapter 6). The outcome, a 4D spatio-temporal map, is then evaluated through real-world experiments and simulations.

1.5 Publications

The work described in each of the following chapters resulted in one or more peer reviewed publications, which are listed bellow.

Chapter 3 provides and overview of the main foundations of this thesis as well as the mains aims of the STRANDS R&D project in which this was carried out. While the models described are not a main contribution of this thesis, their development was influenced by the lifelong exploration strategy proposed in this thesis, resulting in the following publications:

- Krajník, T., **Santos, J. M.**, Seemann, B. & Duckett, T. (2014), Froctomap: An Efficient Spatio-temporal Environment Representation, in 'Advances in Autonomous Robotics Systems: 15th Annual Conference, TAROS 2014, Birmingham, UK, September 1-3,2014. Proceedings', Vol. 8717, Springer, p. 269.

- **Santos, J. M.**, Krajník, T., Fentanes, J. P. & Duckett, T. (2016), Lifelong Information-Driven Exploration to Complete and Refine 4-D Spatio-temporal Maps, IEEE Robotics and Automation Letters 1(2), 684–691.

- Hawes, N., Burbridge, C., Jovan, F., Kunze, L., Lacerda, B., Mudrová, L., Young, J.,Wyatt, J. L., Hebesberger, D., Körtnerr, T., Ambrus, R., Bore, N., Folkesson, J.,Jensfelt, P., Beyer, L., Hermans, A., Leibe, B., Aldoma, A., Faulhammer, T., Zillich,M., Vincze, M., Al-Omari, M., Chinellato, E., Duckworth, P., Gatsoulis, Y., Hogg,D. C., Cohn, A. G., Dondrup, C., Fentanes, J. P., Krajník, T., **Santos, J. M.**, Duckett, T. & Hanheide, M. (2016), 'The STRANDS project: Long-term autonomy in Everyday Environments', in IEEE Robotics & Automation Magazine , vol.PP, no.99, pp.1-1.

In Chapter 4, a description of the several datasets used and a benchmarking tool that enabled the validation of the exploration strategy resulted in the following publication:

- **Santos, J. M.**, Krajník, T., Pulido Fentanes, J. & Duckett, T. (2016), A 3D Simulation Environment with Real Dynamics: A Tool for Benchmarking Mobile Robot Performance in Long-term Deployments, in 'ICRA 2016 Workshop on AI for Long-term Autonomy'.

The concept of lifelong exploration and its experimental validation are described in Chapter 5 can be found in:

- Krajník, T., **Santos, J. M.** & Duckett, T. (2015), Life-long spatio-temporal exploration of dynamic environments, in 'Mobile Robots (ECMR), 2015 European Conference on', pp. 18.

- **Santos, J. M.**, Krajník, T. & Duckett, T. (2016), Spatio-Temporal Exploration Strategies for Long-Term Autonomy of Mobile Robots, 'Robotics and Autonomous Systems', Volume 88, February 2017, Pages 116-126, ISSN 0921-8890.

Finally, the extension of the lifelong exploration concept to real world described in Chapter 6 was published in:

- **Santos, J. M.**, Krajník, T., Fentanes, J. P. & Duckett, T. (2016), Lifelong Information-Driven Exploration to Complete and Refine 4-D Spatio-temporal Maps, IEEE Robotics and Automation Letters 1(2), 684–691.

2

Related Work

This chapter presents a survey of exploration strategies for mobile robots with a focus on the challenges that arise from their long-term deployment in human-populated environments. As stated previously, a mobile service robot requires a model of its operational environment in order to plan its actions in an intelligent and efficient way. The quality of its internal environment model has a significant impact on the robot's ability to localise itself, navigate to the desired locations and perform other tasks in general. Thus, obtaining a model of the environment is an important step to achieve a reliable and robust behaviour of the mobile service robot.

Mobile robotic exploration enables a mobile robot to autonomously build a model of its operational environment which typically consists of two alternating processes: mapping, in which the robot integrates its sensory data into the world model, and planning, during which the robot chooses the actions that would best contribute to improvement of the model. Typical exploration strategies rely on mapping methods that assume the environment to be static, and therefore, the exploration task is finished once all locations have been mapped. However, the environment tends to change over time due to human activity, which causes any static model to become obsolete, affecting the mobile robot performance and possibly even leading to a complete failure of the robotic agent. Lee (1995) states that "world models are only useful if they continue to match the true state of the world" and that a world model is "used to predict the state of the environment so that effective plans can be made". For these reasons, lifelong exploration should use models that allow to represent changing environments and planning methods that can determine not only the locations but also the times of observations in order to maintain the accuracy of the model over time. Moreover, the planning strategy has to take into account different time constraints – it has to schedule the observations in such a way that the robot has time to recharge and can perform its other tasks as well. In order to further investigate these aspects, this chapter provides an overview of both mapping and planning methods for mobile robots.

After presenting an overview of the most relevant mapping and exploration strategies, the challenges in the field of long-term autonomy are identified. Following this analysis, the latest approaches and spatio-temporal world representations that enable long-term autonomy are presented. Finally, a brief discussion on the exploitation/exploration dilemmas specifically for long-term deployments of mobile robots in changing worlds is presented.

2.1 Autonomous Exploration

The ability of mobile robots to autonomously survey in unknown environments, gather data, and to build a model of the environment is called autonomous exploration and typically consists of two interleaved processes: mapping and planning. While the former is responsible for the integration of the perceived data into the current world model, the latter decides where to move next. Robotic exploration strategies take into account both the completeness of the model and its accuracy, because an incomplete and inaccurate world model might compromise the robot's performance (Kollar & Roy 2008).

Mobile robotic exploration strategies can be categorised into map- and non-map-based ones depending on whether it is the model of the environment is used in the planning process or not. Non-map based strategies ignore the knowledge gathered about the world and therefore do not guarantee the completeness of the model in a timely and efficient manner (Sim & Dudek 2003). They can be either based on random movements, such as randomised obstacle avoidance methods, or follows fixed trajectories in which the robot performs circles, spirals, or follow reactive behaviours, such as wall-following (Zhang et al. 2010). Figure 2.1 shows the trajectories obtained by a Roomba autonomous robotic vacuum cleaner while performing randomised obstacle avoidance coverage.

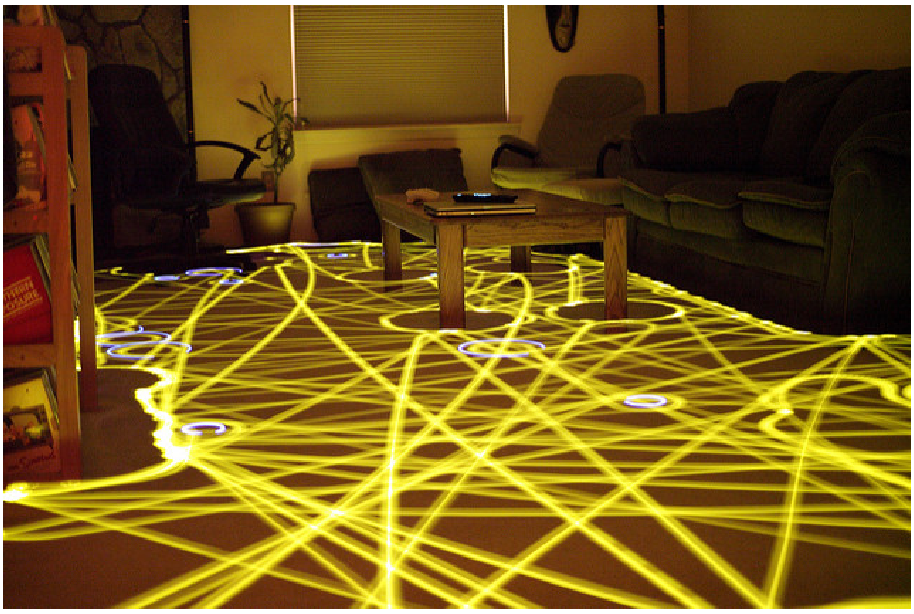


Figure 2.1: *Long-exposure photo showing the trajectory performed by an iRobot Roomba during its autonomous vacuum cleaning task (Roomba 2005).*

On the other hand, map-based-strategies use the world model to identify the unknown areas in the environment and then decide how to observe them while ensuring the model is both complete and accurate in the shortest possible time. Typical examples of these approaches are frontier-based and Next Best View (NBV) strategies. Figure 2.2 summarises the aforementioned categorisation of mobile robotic exploration strategies.

While non-map-based exploration strategies are more suitable for mobile robots with limited computational or sensory capabilities operating in constrained environments, map-based exploration strategies allow to decrease the duration of the mapping task and optimise certain resources, such as the distance travelled or energy consumption.

Frontier-based Exploration Strategies

Frontier-based strategies are one of the earliest exploration methods and were first presented by Yamauchi (1997), who established the term frontier as the boundary between

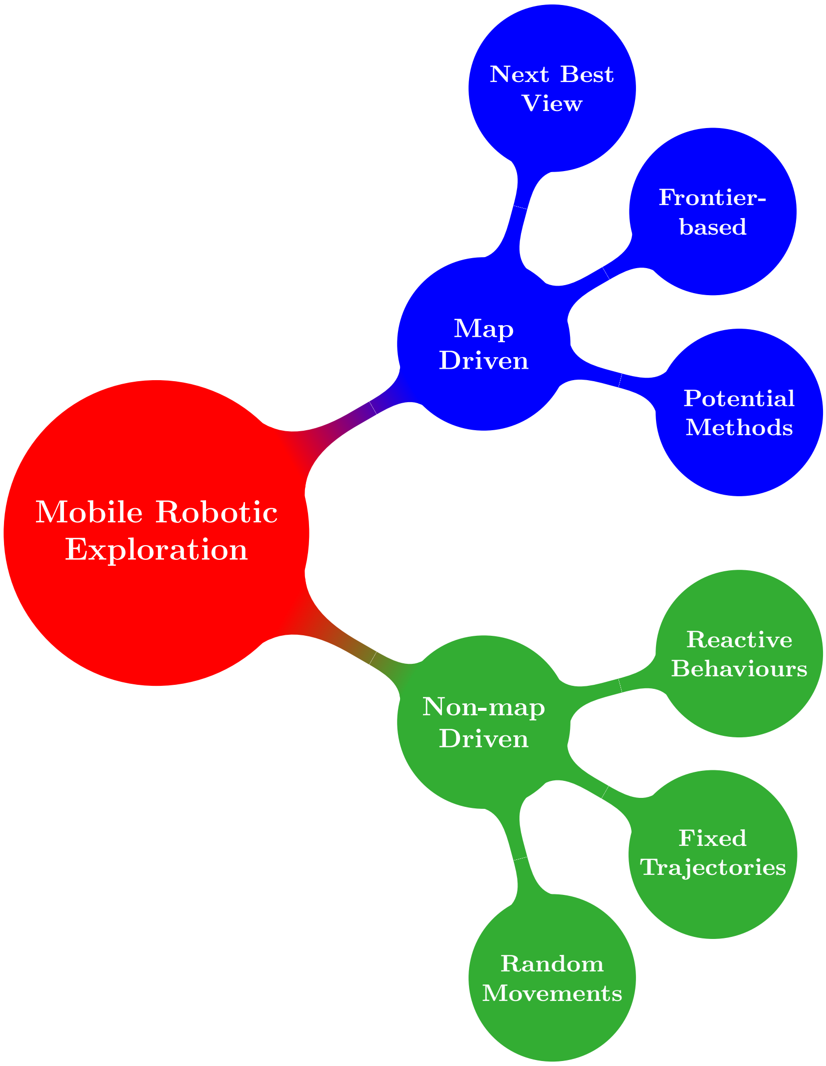


Figure 2.2: *Mobile robotic exploration strategies overview.*

the known and unknown parts of the environment. The frontiers are typically identified using methodologies originating from the use of mathematical morphology in the computer vision domain, but in this case applied to occupancy grids, in which each cell is categorised according to its probability as occupied, unknown, or free. The robot movement is then planned so that these frontiers are visited and removed. Figure 2.3 shows an example of a mobile robot performing frontier-based exploration. The mobile robot transverses a corridor and, in the process, identifies several frontiers. While the method to identify the frontiers is typically the same, the selection of which frontier to eliminate differs from strategy to strategy. The advantage of this approach is its scalability – the frontiers can be distributed among a number of robots that can explore the environment in a cooperative manner (Yamauchi 1998).

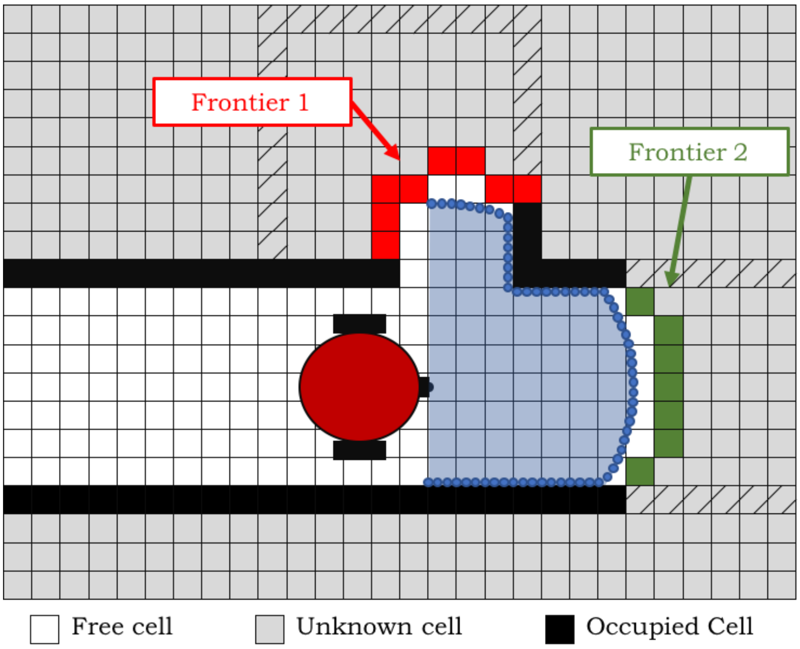


Figure 2.3: *An example of a mobile robot performing frontier-based exploration.*

Holz et al. (2010) presented a survey on earlier frontier-based exploration methods, which is complemented by an experimental evaluation of several strategies. In this study, several issues are pointed out, including: the need to keep a minimum distance to surrounding objects, the need to continuously re-check whether a frontier still exists or not during the navigation task and, finally, the problem of visiting the same room multiple times. For example, looking at Figure 2.3, in the case the mobile robot decides to move along the corridor in order to remove frontier 2, it will need to perform the same path in reverse in order to remove frontier 1 and map the room. On the other hand, removing frontier 1 first would result in a small path diversion and would be the most efficient decision. In order to suppress these issues, the authors propose to segment the current world model into individual rooms and select only frontiers that are within the same room, to verify if there are unknown adjacent cells to the frontier while navigating, and to neglect candidate frontiers that are too close to obstacles. The results obtained through real world experiments show that the proposed improvements allow to significantly decrease the path transversed during the exploration.

Another work that aims at improving the efficiency of frontier-based exploration strategies was presented by Yongguo Mei et al. (2006), which describes a motion planner module that aims at finding trajectories that require low energy. This is achieved by listing all the frontiers within the sensor range and selecting the ones that minimise the number of obstacles in-between the frontiers. Then, a path planning method based on an extended version of Dijkstra's algorithm is applied to a graph in which the vertices represent both the robot's locations and directions between them. Thus, this orientation-based planning method allows to increase the energy efficiency of the robot while travelling between frontiers by decreasing repeated coverage, which is a common issue for this family of exploration strategies. Wirth & Pellenz (2007) propose to extend frontier-based exploration by combining a distance transform with an obstacle transform, i.e., the cost of a path to the closest frontier not only by computing the distance to the frontier but also the distance to the closest obstacle for each cell in the path. This allows the mobile robot to choose not only the shortest but also the safest path to a given frontier, which makes it suitable for Search and Rescue (SaR) scenarios. While in the approach developed by Koenig et al. (2001), the mobile robot does not explicitly determine the frontiers, it moves towards non-explored areas within the sensor range. Other strategies focus on the robustness of the robot's navigation system not only to minimise the robot's localisation uncertainty (Tao et al. 2007) but also to ensure safe navigation to the frontiers (Wettach & Berns 2010).

While the aforementioned works aim at improving the efficiency of frontier-based exploration strategies for a single robot, other authors proposed to extend the concept of frontier-based exploration strategies to teams of multiple robots. On one hand, this allows to decrease the duration of the exploration task, but on the other hand, it requires complex planning methods in order to coordinate the team of mobile robots. Several multi-robot frontier-based strategies that aim at distributing the different frontiers over team of robots are described in (Burgard et al. 2005, Al Khawaldah & Nüchter 2015, Wang et al. 2011, Wurm et al. 2008). The above approaches aim at distributing the frontiers between the mobile robots based on different metrics. By contrast, Renzaglia & Martinelli (2010) propose to use potential fields to naturally coordinate and distribute the robots over all the frontiers by assigning attractive forces to the frontiers and repulsive forces to the robots. In order to decrease the impact of local minima, a team leader is introduced, which in turn can lead to several team leaders according to the mission's evolution.

Recently, a guideline and framework for multi-robot frontier-based exploration benchmarking was presented by Faigl & Kulich (2015). In order to correctly evaluate these strategies, four principles are fundamental: comparison, reproducibility, repeatability and justification. Following these principles, the authors describe a multi-stage methodology that relies on simulations and real world experiments in controllable environments, see Figure 2.4, that enable the evaluation of the exploration strategies using different metrics including, but not limited to, the distance travelled, duration of the exploration task, etc.

(a) The SyRoTek arena.

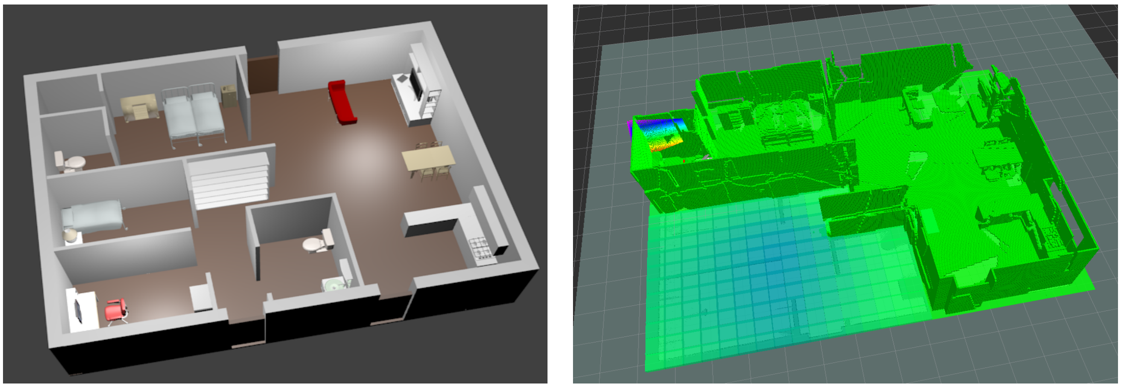
(b) A team of mobile robots performing exploration in the SyRoTek arena.

Figure 2.4: *The SyRoTek reconfigurable arena is available on-line to anyone that intends to evaluate mobile robotic exploration strategies. The user only needs to register, define the number of robots and reconfigure the environment for the experimental evaluation (Kulich et al. 2013).*

The aforementioned methods all use the same definition of frontier and they differ only in the way these frontiers are used for planning either single or multi-robot. While the way frontiers are calculated and identified is the same in every strategy, the order and distribution of visits following different metrics are the main contributions.

Next Best View Exploration Strategies

Since frontier-based exploration aims primarily at exploring the physical space by removing all the frontiers until the model completeness is guaranteed, they do not ensure the quality of the map. On the other hand, Next Best View (NBV) strategies can take into account both completeness and accuracy. They are based on the notion of entropy, i.e., the set of candidate locations to observe is computed based on the estimated amount of information each of these locations is expected to provide (Caglioti 2001). The most remarkable advantage of these methods is the possibility to specify several objectives by means of cost functions, such as the travelled distance, repeated coverage, quality of the observations, etc. Thus, these approaches can be adapted to different types of missions and applications by setting up the proper metrics. The information gain is calculated as the reduction in entropy of the world model, which requires a probabilistic representation of the environment states. The lower the entropy of the environment model, the more it reflects the actual environment state. More details on the concept of entropy and information are given in Chapter 3. Figure 2.5 shows a mobile robot performing NBV exploration in a domestic environment. In order to identify the most entropic locations, the information-gain values are projected onto the ground plane. The Figure 2.5b shows that these values are higher in the centre of the unexplored area.



(a) 3D render of a domestic environment. *(b) The outcome of an information-based exploration strategy.*

Figure 2.5: *The mobile robotic platform performs information-based exploration in a house-like environment. The expected information-gain is projected on the ground plan. The blue cells indicate locations where the expected information-gain is higher.*

Stachniss et al. (2005) presented an information gain-based exploration framework that integrates not only uncertainties of the map but also the uncertainties of the robots localisation. The exploration method uses a Rao-Blackwellized particle filter to build the map of the environment and an entropy reduction method to plan the next location to be visited by the robot. An analogous strategy was presented previously by Makarenko et al. (2002). In this approach, the robot performs two different types of exploration tasks: one to integrate new observations into the model and thereby complete it, and another one that plans where to re-observe in order to close the loop and, consequently, reduce the robot's pose uncertainty. Similarly, Amigoni & Caglioti (2010) propose an information-based strategy that proposes the next location to observe based not only on the expected entropy reduction but also on the distance travelled. The above strategy was then extended to Search and Rescue (SaR) missions (Basilico & Amigoni 2011). Another approach that aims at improving the accuracy of environment model is proposed by Kollar & Roy (2008), in which a skeleton graph is obtained from the current environment model, which is then used to search for an optimal path by taking into account the sensing constraints at each node.

NBV strategies to build 3D models of outdoor scenarios based on information-gain methods were proposed by Fentanes et al. (2011). A cost function is used in order to maximise not only the information-gain but also the model's quality and optimising the robots trajectory, i.e., instead of choosing the next location to observe, the mobile robot also takes into account the sensor's model and the angle of observation in order to obtain a very precise 3D model of the different objects in the environment. An advantage of this method is that it not only attempts to cover the entire environment as quickly as possible but also plan re-observations of previously visited locations to increase the quality of the resulting map.

Analogous to the frontier-based approaches, NBV approaches have been extended to teams of multi-robots. Burgard et al. (2005) presented an information-based exploration strategy that assigns robots to different locations to observe based on their trade off between the cost to reach the desired location and the expected information-gain. Nevertheless, this approach assumes all the robots know their relative positions to each other. Other strategies rely on semantic information in order to distribute the mobile robots through the different points in order to reduce redundant coverage (Stachniss et al. 2006).

Alternative Exploration Strategies

Although the exploration strategies described above fit in two very specific categories there are other strategies that do not fall in these categories, but are still relevant. For example, potential methods, in which a high potential is assigned to the start position and a low potential assigned to the goal position. Then, a gradient is computed through the resulting field and used to drive the robot through the unexplored areas of the environment. Following this principle, Junior et al. (2002) propose an exploration strategy based on potential fields modelled by means of harmonic functions and relying exclusively in Dirichlet boundary conditions. These harmonic functions do not generate a local minima and, consequently, the robot does not get trapped when performing exploration. The authors have successfully shown the exploration of 2D environments with a sonar equipped mobile robot using potential fields. Another strategy based on potential fields is proposed by Shade & Newman (2011), in which stereo vision cameras are used to perform visual Simultaneous Localisation and Mapping (SLAM) and potential fields used to drive the robot to unexplored areas. The proposed strategy exploits the properties of harmonic solutions and Laplace's equation in order to find a scalar field that does not contain a local minima. Other strategies combine potential and information-based methods in order to perform exploration, such as the multi-robot exploration strategy proposed by Rocha et al. (2005). This strategy, which combines the concept of frontier with information-theoretical approaches by means of gradient-based representation, allows to achieve 3D maps with lower uncertainty. The entropies for each cell in the 3D grid are calculated and then a continuous entropy field is sampled over each voxel. Finally, each robot selects observation points with higher entropy gradient, which are located at the frontiers between the explored and unexplored areas. A mutual information-based measure of information utility is proposed in order to efficiently coordinate the team of multiple robots.

Other exploration strategies aim at building maps of the environment taking into account some *a priori* knowledge instead of building it from scratch. For instance, Obwald et al. (2016) propose a novel exploration strategy that aims at decreasing the exploration time by assuming that the topology of the environment is known, such as graphs automatically obtained from floor plans. In this method a Travelling Salesman Planner generates a global plan for the exploration run while a frontier-based strategy is used to explore the environment at each node of the graph. Fox et al. (2003) propose a learning process that takes into account several maps to build a structural model of "typical" environments. This model consist of a hidden Markov model that generates sequences of views observed by a robot when navigating through an environment. The model is then used by the mobile robot to identify whether is exploring a new area or revisiting a previously explored area. Similarly, Strom et al. (2015) present an exploration strategy capable of predicting how the unexplored areas may look based on previously mapped areas. This strategy combines the knowledge obtained through previous exploration tasks (in different environments) to predict which observation points might close the loop with information-driven exploration to map the environment more efficiently.

Some strategies are based on intrinsic motivation systems, which drive the robot towards situations that maximise the performance of the learning process (Oudeyer et al. 2007, Thrun 1992). These strategies are able to actively identify anomalous or novel situations that might lead to decisions that provide more information and allows to deal with situations where the information gain never decreases due to physical constraints such as occlusions. For example, novelty detection strategies, which involve the recognition of environmental stimuli that differ from those usually seen, allow the robot to gradually redirect its attention according to the evolution of its internal models (Marsland 2002).

The aforementioned exploration strategies aim at building a map of the environment in the initial stage of the robot deployment, but are not aimed at maintaining it over time, ignoring the changes in the environment. Thus, the model accuracy will decrease as the environment changes, which would eventually lead to major localisation and navigation failures.

2.2 Environment Representations for Mobile Robots

The aforementioned exploration strategies are highly dependent on the type of representation used. Most of the environment models and methods that create them are tailored to represent static scenes and treat environment dynamics as unwanted noise. Thus, previous research on mobile robot exploration was aimed at efficient acquisition, representation and usage of static environment models, which can range from geometrical representations, such as vector maps, to more high-level representations like topological maps. Before describing environment representations that can cope with the environment changes, an overview of classical environment models is given.

Classical Environment Representations

Two of the most popular methods that use a different level of abstraction are metric and topological maps. Perhaps the most known and used metric map is the occupancy grid which was proposed by Moravec (1988). This representation allows for efficient probabilistic sensor fusion, motion planning, localisation and exploration. The main drawback of occupancy grids is their low-memory efficiency since they represent large, empty areas of the environment by a large number of empty cells. A popular approach that mitigates the low memory efficiency of occupancy grids is the quadtree (Finkel & Bentley 1974, Chen et al. 2015). It represents the environment in a tree-like structure that recursively subdivides a region until it does not contain any object. OctoMaps extend the above representation to 3D (Hornung et al. 2013). An example of an OctoMap is shown in Figure 2.6. Compared to occupancy grids, vector maps provide better memory efficiency (Sohn & Kim 2009). These maps represent the environment by means of a set of segmented lines or polygons; however, this representation is only suitable for structured indoor environments.

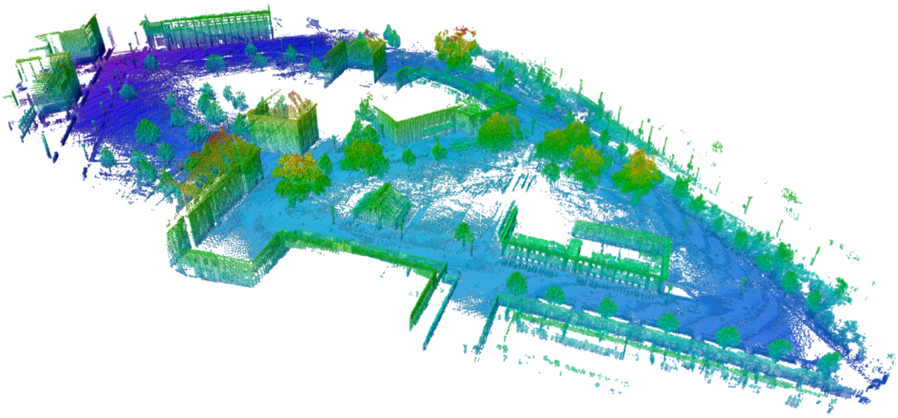


Figure 2.6: *Example of an OctoMap (Hornung et al. 2013).*

Topological maps represent the environment by means of graphs, in which each node corresponds to a distinct situation, place or landmark and the edges represent the paths between the nodes (Thrun 1998). Due to their compactness, topological maps also provide the ability to efficiently store additional information in both edges and nodes that allow to extend the robot capabilities. For instance, Fentanes et al. (2015) propose to learn the different edge traversability times in order to improve the robot's navigation performance. While this representation enables efficient planning and memory management, compared to occupancy grids, it requires complex methods in order to build and maintain the maps in large-scale environments.

Other representations model the robot's operational environment as set of landmarks and their geometric positions (Montemerlo et al. 2002, Choudhary et al. 2015). While in topological maps the nodes relative positives are stored and used for localisation and navigation from a node to another, the positions stored in landmark maps are global, i.e., within the same reference frame.

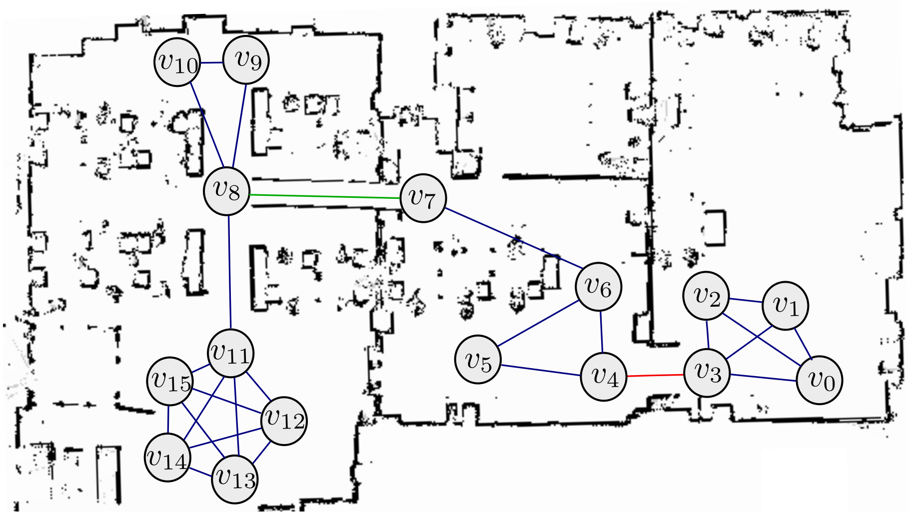


Figure 2.7: *Example of a topological map over an occupancy grid (Fentanes et al. 2015).*

While the aforementioned world models rely exclusively on an environment representation, some authors propose to combine the advantages of different environment representations to improve the performance of mobile robots in large environments. A remarkable work on hybrid representations is presented by Kuipers & Byun (1991), which proposes to use a hierarchical description of the environment based on a metric, topological, and semantic level. In this model, the different locations in the environment are described using not only their metric coordinates but also the different features. The role of the topological level is to establish a relationship between the different locations and representations. Based on the previous paradigm, Bosse et al. (2003) developed the *Atlas* framework, which demonstrated its ability to represent large environments. Krajník et al. (2010) showed that a topological/landmark based representation allows ground and aerial robots to reliably operate in a large outdoor environment over long periods of time.

Strategies and Environment Representations for Changing Environments

Once robots have attained the ability to operate for longer periods of time, the effects of the environment changes have to be taken into account. The previously described models represent the environment as a static structure, an assumption which tends to be violated during long-term deployment of mobile robots in human-populated environments. Thus, to achieve long-term autonomy, a robotic agent must be able to deal with and adapt to the environment changes, which can be achieved by modelling the environment without ignoring the dynamics.

The first approaches that attempted to model environment changes were aimed at short-term changes. In these methods, dynamic objects are identified and then removed from the world model (Hahnel et al. 2002, Wolf & Sukhatme 2005), other approaches used these dynamic objects as moving landmarks (Wang et al. 2007). However, some dynamic objects do not move at the time of mapping and, consequently, the robot needs further observations to identify them. Ambrus et al. (2014) propose to process several 3D point clouds of the same environment obtained over a period of several weeks to separate movable objects and refine the model of static environment structure at the same time. The resulting model of the static part of the environment is named metaroom and an example is shown in Figure 2.8.

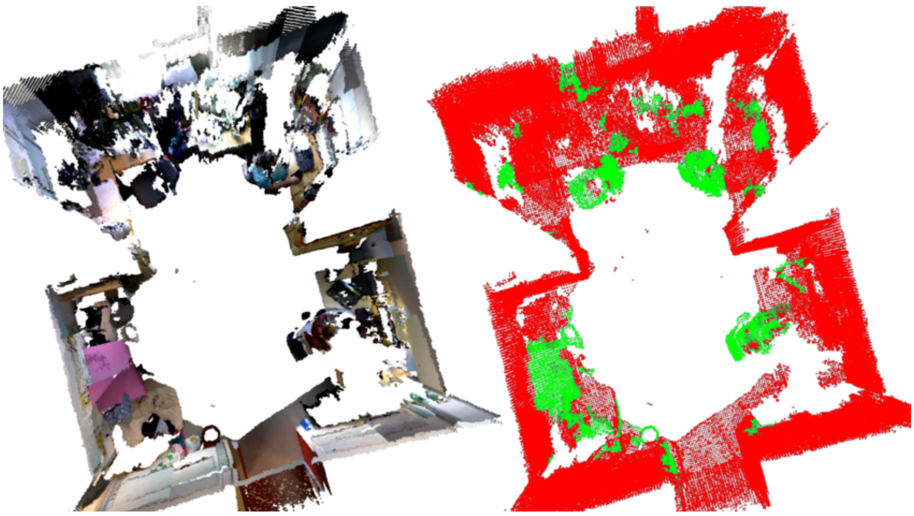


Figure 2.8: *Example of a metaroom (Ambrus et al. 2014).*

Other approaches do not explicitly segment movable objects but use representations that are able to model large-scale, substantial environment changes over long time periods. Some authors (Biber & Ducket 2009) represent the environment dynamics by multiple temporal models with different timescales, and Dayoub & Duckett (2008) use a ranking scheme that allows to identify environmental features that are more likely to be stable in long-term. Churchill & Newman (2013) propose to cluster similar observations at the same spatial locations to form 'experiences' which are then associated with a given place and show that this approach improves autonomous vehicle localisation. Tipaldi et al. (2013) represent the states of the environment components (cells of an occupancy grid) with a hidden Markov model and show that their representation also improves localisation. Similarly, in the model proposed by Saarinen et al. (2012), each cell in the occupancy grid stores not only the probability of it being occupied but also the likelihood of the cell to change after a given time. Kucner et al. (2013) propose a method that learns conditional probabilities of neighbouring cells of an occupancy grid to model typical motion patterns in dynamic environments. Neubert et al. (2015) proposed a method that can learn appearance changes based on a long-term dataset collected across multiple seasons and use the learned model to predict the environment appearance for a given time. Another approach that possesses the ability to predict environment changes is proposed by Rosen et al. (2016), which uses Bayesian-based survivability analysis to predict which environment features will still be visible after some time and which features will disappear.

Another family of algorithms aims at creating models of the environment that allow them to predict where and when to make observations of specific phenomena within the environment. Typically, these algorithms rely on Gaussian Processes (Singh et al. 2010, Marchant & Ramos 2012), which allow the robot to learn patterns of environment changes. Even though these approaches are able to build models of given phenomena, these models are not used by the robot itself to improve essential competences such as localisation.

Biswas & Veloso (2017) propose to model and classify the environment changes in order to improve the robot's localisation during its long-term deployment. For this purpose, a Varying Graphical Network is used to learn and classify the different types of changing features in the environment. These can range from short-term to long-term features or even static ones. This model is then combined with an episodic non-Markov algorithm that maintains beliefs of the previous pose estimates of the robot when observing unmapped objects. This results in a decrease of the robot's localisation uncertainty when exposed to environment changes.

Finally, Krajník et al. (2014a) propose to represent the environment dynamics in the spectral domain and apply this approach to image features to improve localisation (Krajník et al. 2014b), to occupancy grids to reduce memory requirements (Krajník et al. 2014c), and to topological maps to improve both path planning (Fentanes et al. 2015) and robotic search (Krajník et al. 2015a). While being applicable to most environment models used in mobile robotics, the aforementioned method suffers from a major drawback due to its reliance on the traditional Fast Fourier Transform (FFT) method, which requires the environment observations to be taken on a regular and frequent basis. This means that the robot's activity has to be divided into a learning phase, when it would frequently visit individual locations to build its dynamic environment model, and a deployment phase, when it would use its model to perform useful tasks. This division means that while the robot can create dynamic models, which are more suitable for long-term autonomy, it cannot maintain them during subsequent operation. Thus, the robot does not adapt to dynamics that were not present during the learning phase. This model is discussed in more detail in Chapter 3.

2.2.1 Exploitation vs. Exploration Dilemma

On one hand, the mobile robot needs to perform useful tasks and increase its performance by exploiting its internal models, but on the other hand, these models need to be learnt and kept up to date during the entire deployment. The long-term deployment of mobile robots in human-populated environments must take into account the need to balance exploitation of what the robot already knows and exploration that allows to select better actions in the future (Sutton & Barto 1998). This issue is addressed by Hawes et al. (2016), which describes a long-term deployment of a mobile robot in a care centre. Several tasks need to be performed by the robot but there is one that directly addresses the exploration/exploitation dilemma (Hanheide et al. 2017). Here, the mobile robot has to act as an information terminal providing information services to visitors. This task is scheduled at different locations in order to increase the number of interactions. However, the scheduler must address two different objectives: exploration and exploitation. The first one creates and maintains a spatio-temporal model of the interactions, providing interaction likelihoods for the different locations and times. The second one aims at visiting the different locations at times when the likelihood of observing interactions is uncertain. Based on the above work, Kulich et al. (2016) developed and evaluated several exploration/exploitation strategies, environment models, and path planning algorithms to increase exploitation, or more specifically, to increase the number of interactions with humans.

In order to increase the interactions, the robot needs to learn human behaviours, more specifically where and when it is more likely for a human to ask for assistance. However, this needs to be achieved in parallel with the human interactions as well as the other robot's daily tasks.

2.3 Summary

Related work on mapping and planning strategies for human-populated environment has been presented in this chapter. Several concepts and issues involved in exploration strategies and the existent world models have been introduced and analysed. This is fundamental to understand the need for novel strategies and models that can cope with environment changes and consequently enable long-periods of autonomous operation. Although the field of long-term autonomy is still recent, most of the challenges and guidelines to overcome them were firstly presented by Austin et al. (2001). The authors claim that only when a "system that can run 24 hours a day, 7 days a week for up to a year with no supervision" is achieved, the field of mobile robotics has reached "maturity". Another relevant point, which is also the main motivation of this thesis, is that mobile robots must be able to deal with dynamic environments not only to detected dynamic objects, such as people, but also to localise in a changing environment and to maintain a world model over time. Finally, the same way humans spend time studying and learning about nature and its physical phenomena, the long-term deployment of mobile robots allows to gather data that, consequently, enables a mobile robot to learn about its environment.

Recently, Cadena et al. (2016) presented a survey that not only covered the current state of SLAM strategies but also their scalability to long-term mapping and the future of these strategies. New research questions that enable the development of autonomous self-learning mobile robots in changing environments are presented, such as the need to develop SLAM approaches that are fail-safe and failure-aware, approaches that automatically learn the best parameters while performing the mapping task and finally the ability to cope with the environment changes in order to operate over long periods of time. While not directly addressing all aforementioned issues, Biswas & Veloso (2016) have shown that self-learning systems that aim at understanding environment changes enable the successful operation of mobile robots over long periods of time.

Having this in mind, in the next chapter, the main foundations that support lifelong exploration strategy proposed in this thesis are described. These foundations are in line with the above considerations on the field of long-term autonomy.

3
Main Foundations

This chapter provides a detailed description of the methods and models used in the development of the proposed lifelong exploration strategy. As stated previously, a map-driven exploration strategy aims at building a model of an unknown environment, which is then used by a mobile robot to decide where to perform the following observations. Thus, the development of any map-driven exploration strategy has to take into account the way the robot's operational environment is represented. The lifelong exploration for mobile service robots proposed in the scope of this thesis was built upon a spatio-temporal model named Frequency Map Enhancement (FreMEn) (Krajník et al. 2014a), which enables the extension of information-based concepts into time and, consequently, enables the mobile robot to predict how much information it will obtain by observing a specific location at a given time and, therefore, decide where and when to observe the environment. While the aforementioned model is not the main contribution of this thesis, due to the simultaneity of its development, it was highly influenced by the requirements of lifelong exploration. Not only does the lifelong exploration strategy require a spatio-temporal representation that can model the environment states over time and reason about when and where to make new observations but the model itself requires the possibility of efficient integration of sparse and irregular observations gathered over long periods of time.

This chapter is crucial to understand the concepts and methods used in this thesis and is organised as follows. Firstly, an overview of the collaborative project which this thesis is part of is conducted, giving an overview of the goals and allowing to contextualise the different methods used in the development of the lifelong exploration strategy as well as the experimental conditions. Secondly, a detailed description of the FreMEn model on which the proposed exploration was built is presented. Finally, the concept of information, data and entropy are explained and linked to the aforementioned spatio-temporal model.

3.1 The STRANDS Project

This thesis was carried out as part of the STRANDS R&D project funded under the European Community's Seventh Framework (FP7/2007-2013), grant agreement No. 600623. This section provides a brief description of the project and its aims, which contributed to establishment of the goals and contributions of the work presented in this thesis. The main aim of the STRANDS project, which stands for Spatio-temporal Representation and Activities for Cognitive Control in Long-term Scenarios, is to enable mobile robots to intelligently adapt and operate over long periods of time in human-populated changing environments by learning from their long-term experience (Hawes et al. 2016).

To achieve long-term adaptive behaviour in changing environments, the mobile robot has to understand how the environment changes while at the same time exploit the knowledge that is obtained through the entire duration of its deployment. The long-term deployment not only enables the mobile robot to experience novel and unexpected situations, but also provides the opportunity to learn how to adapt to them. Figure 3.1 presents an overview of the STRANDS system. In this system, the robot takes actions in a never-ending lifelong learning phase that happens while performing its duties, i.e. the mobile robot is continuously learning from its experience. Thus, the exploitation of the long-term knowledge gathered during this life-long learning stage allows the mobile robot to identify patterns of change and recurring events in the environment that are then used to improve the robot's performance. These patterns can be identified in several domains that range from human activities to objects or even certain physical phenomena.

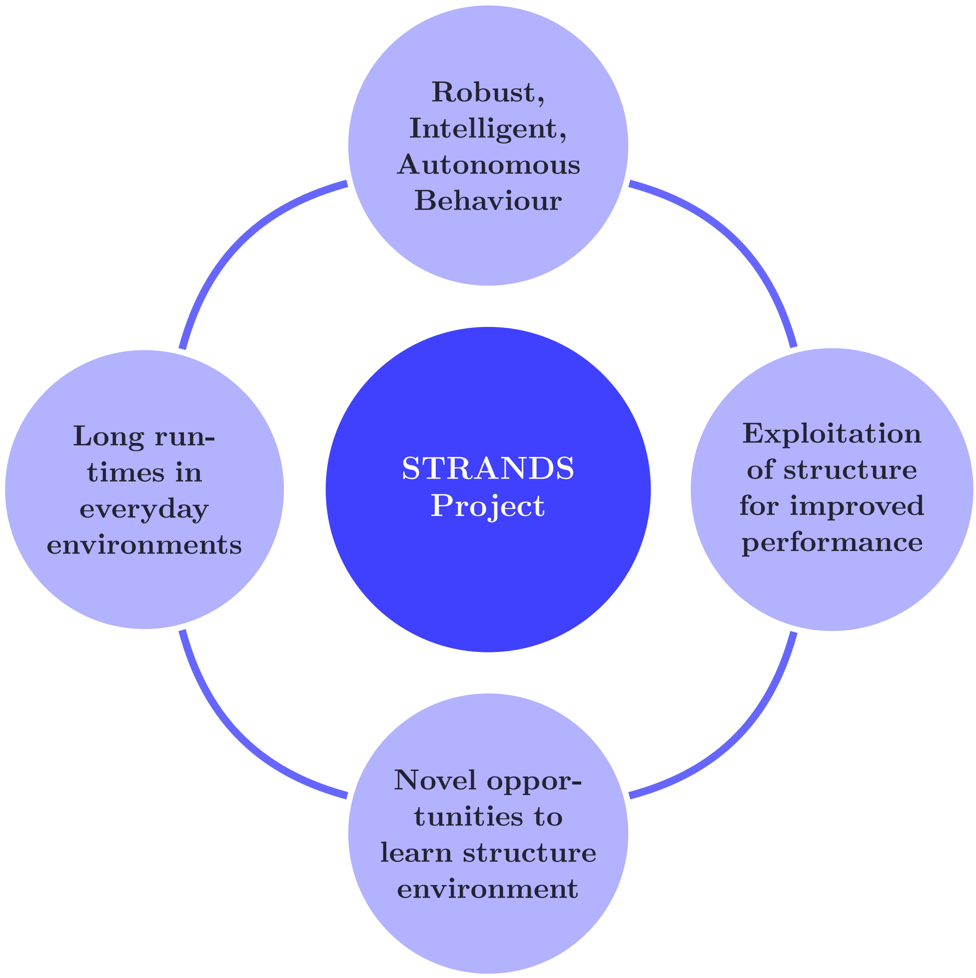


Figure 3.1: *The STRANDS project overview (Hawes et al. 2016).*

The system developed in the scope of the STRANDS was entirely developed using the Robot Operating System (ROS) framework. It consists of several layers, where each layer provides different levels of knowledge abstraction. These layers range from perception, navigation and localisation, executive control to representation and analysis. Due to the nature of the STRANDS system, the exchange of information happens in both ascending and descending ways, i.e., the lower layers provide knowledge to the top layers and the top layers provide methods that enable the robot to improve its own knowledge and behaviour.

All the methods developed in the scope of the STRANDS project are evaluated in two highly challenging real-world scenarios: a security scenario and a care scenario. In both scenarios, the robot needs to perform tasks that benefit the end-user without having a negative impact on the end users' daily routines. The deployment in the security scenario took place at G4S headquarters in Crawley, United Kingdom, during the first two deployments and later on at the Transport Systems Catapult offices in Milton Keynes, United Kingdom, as shown in Figure 3.2a. As part of the security deployment, some of the mobile robot tasks include learning how the environment changes, learning to identify and segment the dynamic parts in the environment from the static ones, learning the objects' appearance and also people. While the security scenario does not provide many chances for the robot to fully interact with humans while performing different tasks, the care scenario represents a more complex environment, where people with different disabilities and different cognitive capabilities are found. The care scenario took place in a care home named "Haus der Barmherzigkeit" situated in Vienna, Austria, as shown in Figure 3.2b. In the care scenario, the robot takes an active part in some of the activities available for the patients, playing a key role in the therapies while enriching the experience for both patients and staff. For example, walking activities are carried out every week in order to keep the residents active but also to stimulate them cognitively. In this specific example, the robot takes part of the activity by playing songs and displaying several activities on its display that allow the patients to interact with while also enriching the interaction between patients and patients and the therapists. Other relevant task included using the mobile robot as a mobile info-terminal that displays relevant information in the different locations of the care home.

While in this scenario most of the robot's duties imply human-robot interaction, the security scenario aims at learning objects from changes observed in the robot's sensor data. The complexity of tasks in this scenario is significantly higher due the nature of the environment and people involved. At the moment, the security scenario aimed at learning objects, while the care scenario aimed at interacting directly with the assisting therapists and patients. The robot has been deployed in both scenarios over several weeks, increasing the deployment times gradually from year to year. For the first year, the deployments took 15 days and were aimed at patrolling tasks and detecting people and environment changes. The second year deployment took 30 days and was aimed and detecting human activities, creating Qualitative Spatial Representations (QSR) and learning objects. Finally, the last two deployments with durations of 60 and 120 days were aimed at exploiting the robot's knowledge in order to predict environment changes, learn about objects and detect usual events and activities.

(a) Security scenario. *(b) Care scenario.*

Figure 3.2: *Photos of the real-world environemnts used in STRANDS.*

3.2 Spectral-based Temporal Representations

Many mapping approaches assume that the principal components of a particular environment model are independent and can be in two distinct states. For example, cells of an occupancy grid are occupied or free, edges of a topological map are traversable or not, doors are opened or closed, rooms are vacant or occupied, landmarks are visible or occluded, etc. In a typical situation, the state of each model component is uncertain because it is measured indirectly by means of sensors which are affected by noise. A common way to represent the uncertainty in the state estimate of the j^{th} world model component is by its associated probability p_j. This allows to counter the effect of noisy measurements by employing statistical methods, such as Bayesian filtering. While Bayesian filtering methods allow to keep up with a changing environment, the mathematical foundations they are based on assume a static world, i.e. the p_j of the world components are assumed to be constant. As a result, a change in the environment causes the old state to be “forgotten” over time.

Assuming p_j as a function of time leads to the need to outline a suitable representation for $p_j(t)$. Although one could simply store the entire history of the environment model, such an approach would quickly face memory limitations. Typical static 3D models of complex environments contain millions of distinct components and storing the entire model history is infeasible. Moreover, in the context of robotic mapping, it is not clear how to utilize the past estimates of the environment models, i.e. what is the relation of the past models to the current state of the world.

The approach described in the section assumes that the variations of the environment are caused by a number of unknown processes, which might be periodical. Thus, by identifying the influence and periodicity of these processes, the probabilities $p_j(t)$ can then be obtained from their description.

The Fourier Transform (FT) is a well-established mathematical tool widely used in the field of statistical signal processing. It transforms a function of time $f(t)$ into a function of frequency $F(\omega)$, i.e. $F(\omega)=\mathcal{F}(f(t))$. The function $F(\omega)$ is commonly referred to as the frequency spectrum of $f(t)$. The FT is invertible, and therefore, one can recover the function $f(t)$ from its spectrum $F(\omega)$, i.e. $f(t) = \mathcal{F}'(F(\omega))$. If one wants to analyse or alter the periodic properties of a process characterized by a function $f(t)$, it is possible to calculate its spectrum $F(\omega)$, perform the analysis or alteration in the frequency domain, and then transform the altered spectrum $F'(\omega)$ back to the temporal domain. Such a process is referred to as spectral analysis.

Typically, $F(\omega)$ is a complex-valued function, whose absolute values and arguments correspond to the amplitudes and phase shifts of the frequency components ω. Considering that $f(t)$ is a real periodical discrete function, the spectrum $F(\omega)$ can be represented by a finite set of complex numbers. More details about the FT and Discrete Fourier Transform (DFT) are given in Appendix A.

3.2.1 Notation

To describe the spectral model used in this thesis, the following notation is used:

- s_j denotes the state of the i-th cell in a grid;
- p_j denotes the probability of the i-th state in a grid;
- l denotes the set of most prominent coefficients;
- $\mathcal{S}$ denotes the set of world states;
- $\mathcal{P}$ denotes the set of prominent coefficients;

- $\mathcal{O}$ denotes the set of outliers;
- ς denotes a saturation function;
- ω denotes the angular frequency;
- $\mathcal{A}$ denotes the frequency spectrum of observations;
- $\mathcal{B}$ denotes corrective spectrum;
- $\mathcal{C}$ denotes the corrected frequency spectrum;
- α denotes the components of spectrum of observations;
- β denotes the components of corrective spectrum;
- μ denotes the mean probability;
- H denotes the information gain.

3.2.2 Frequency Map Enhancement

For simplicity, this approach will be explained using an occupancy grid, which is represented as a set of independent components that can be in two distinct states. Each grid cell state $s_j = \{occupied, free\}$ is assumed not to be constant, but a function of time, i.e. $s_j(t)$. Consequently, the uncertainty of the state $s_j(t)$ is represented by its probability $p_j(t)$. Additionally, working under the assumption that the occupancy of each grid cell is affected by a set of unknown periodical processes, which can be identified by the FT, and that the occupancy of individual cells is independent from each other, the Fourier transform on the state $s(t)$ of a single cell will be demonstrated in the following section.

The spectral model

The main idea behind the proposed model is to measure the temporal sequence of states $s(t)$ and calculate their frequency spectrum by means of a FT as $\mathcal{S}(\omega) = \mathcal{F}(s(t))$. Then, the l most prominent (i.e. of highest absolute value) coefficients S_i of the spectrum $\mathcal{S}$ are selected and stored along with their frequencies ω_i in a set $\mathcal{P}$. The function coefficients stored in $\mathcal{P}$ are then used to recover the $p(t)$ by means of the Inverse Fourier Transform $p(t) = \varsigma(\mathcal{F}'(\mathcal{P}(\omega)))$, where ς denotes a saturation function that ensures that $p(t) \in <0, 1>$.

One can easily verify that $P(s(t) = \mathit{occupied}) = p(t) \geq 0$ and $P(s(t) = \mathit{occupied}) + P(s(t) = \mathit{free}) = p(t) + 1 - p(t) = 1$, i.e. $p(t)$ satisfies Kolmogorov's axioms and therefore is a probability. Thresholding the probability $p(t)$ allows to calculate an estimate $s'(t)$ of the original state $s(t)$. In order not to lose any information of the original signal, the differences between $s'(t)$ and $s(t)$ are stored in an outlier set $\mathcal{O}$, which is Δ-encoded, see Figure 3.3.

Thus, the proposed model of the state consists of two finite sets $\mathcal{P}$ and $\mathcal{O}$. The set $\mathcal{P}$ consists of l triples $abs(P_i)$, $arg(P_i)$ and ω_i, which describe the amplitudes, phase shifts and frequencies of the model spectra. Each such triple might be interpreted as the importance, time offset and periodicity of one particular periodical process influencing the state $s(t)$. The number of modelled processes l (i.e. the number of triples in $\mathcal{P}$) is referred to as the 'order' of the spectral model. The set $\mathcal{O}$ represents a set of k time intervals, during which the state $s(t)$ did not match the state $s'(t)$ calculated from $p(t)$. Internally, the set $\mathcal{O}$ is implemented as a sequence of values, indicating the starts and ends of time intervals when the predicted and observed state did not match, i.e. $s'(t) \neq s(t)$.

Model adaptation

To be able to build, maintain and use this representation, four operations are defined: reconstruction of the original state $s(t)$, addition of a new measurement, model update and prediction of the future state with a given confidence level. The aforementioned representation allows to retrieve the cell state $s(t)$ by means of the following equation:

$$s(t) = (\mathcal{F}'(\mathcal{P}) > 0.5) \oplus (t \notin \mathcal{O}), \tag{3.1}$$

where $\oplus$ is a XOR operation. The idea behind this equation is to reconstruct the probability $p(t)$ from the spectrum $\mathcal{P}$, set $s(t) = 1$ if $p(t)$ exceeds 0.5 or $s(t) = 0$ otherwise and finally, to negate $s(t)$ if t belongs to the set of outliers $\mathcal{O}$.

Whenever a real state $s^m(t)$ is measured, $s(t)$ is calculated by means of Equation (3.1) and if it differs from $s^m(t)$, the current time t is added to the set $\mathcal{O}$:

$$s^m(t) \neq ((\mathcal{F}'(\mathcal{P}) > 0.5) \oplus (t \notin \mathcal{O})) \rightarrow \mathcal{O} = \mathcal{O} \cup t. \tag{3.2}$$

Since $p(t)$ does not predict $s(t)$ with perfect accuracy, the set $\mathcal{O}$ is likely to grow larger as measurements are added.

To update the model, $s(t)$ is reconstructed in the desired time interval $< t_{start}, t_{end} >$ and its spectrum $\mathcal{P}$ calculated. Again, the l coefficients with highest absolute values $|P_i|$ are selected and the outlier set $\mathcal{O}$ reconstructed by means of Equation 3.2. In a typical situation, the updated spectrum $\mathcal{P}$ would reflect $s(t)$ more accurately, causing reduction of the set $\mathcal{O}$. Note that the spectral model order l of the updated model can differ from the order of the original one.

The outlier set $\mathcal{O}$ described above is part of the original FreMEn model description and allows to fully reconstruct the original signal. Thus, it is only described to fully understand the foundations of the FreMEn and not used in the development of the lifelong exploration strategy.

Prediction

Note that Equation (3.1) allows for calculating $s(t)$ for any t and that the threshold value of 0.5 can be set arbitrarily. In fact, a threshold c such that $P(s(t) = occupied) > c$ represents a confidence level of the grid cell being occupied at time t. Therefore, Equation (3.1) can be used for future prediction of $s(t)$ with a certain confidence level c. In the case of prediction, the outlier set $\mathcal{O}$ is not included in the calculation and the predicted state might not match the real state, so it is denoted $s'(t, c)$. To simplify notation, $s'(t)$ is defined as $s'(t, 0.5)$. Therefore, $s'(t, c)$ and $s'(t)$ can be calculated as follows:

$$s'(t, c) = \mathcal{F}'(P) > c. \tag{3.3}$$

An example of the third-order spectral model which represents a quasi-periodic function is provided in Figure 3.3. Since the observed processes are not identified perfectly, one can expect that the prediction becomes less and less accurate over time. However, modelling the uncertainty of the model prediction is outside the scope of this thesis. More details about this spatio-temporal representation can be found in video created by Krajník et al. (2015b).

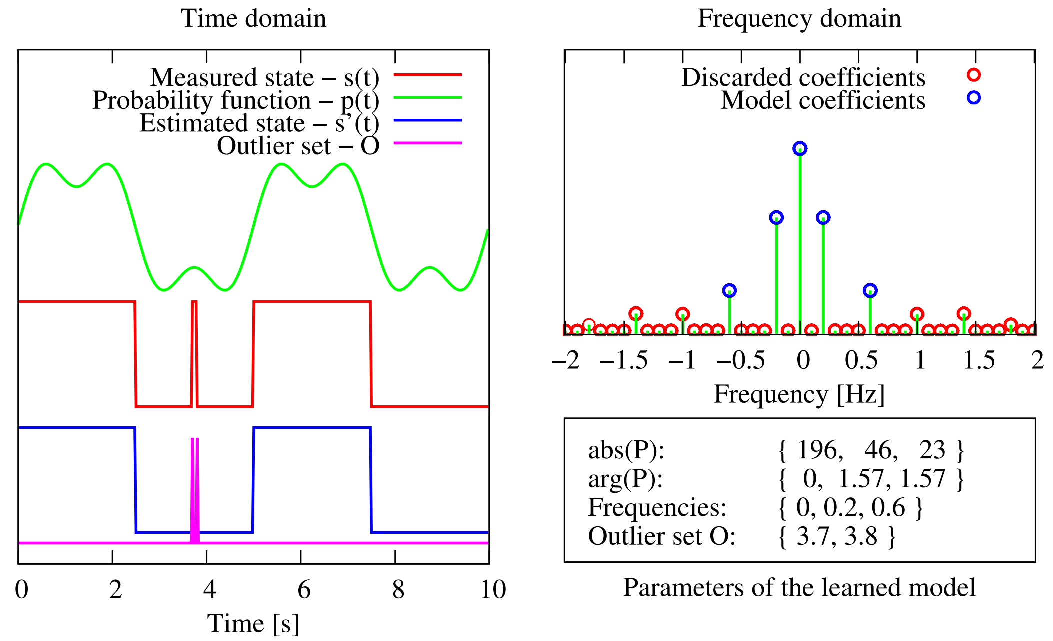


Figure 3.3: *An example of the measured state and its spectral model. The left part shows the time series of the measured state $s(t)$, probability estimate $p(t)$, predicted state $s'(t)$ and outlier set $\mathcal{O}$. The upper right part shows the absolute values of the frequency spectrum of $s(t)$ and indicates the spectral coefficients, which are included in the model.*

3.2.3 FreMEn: Non-uniform Sampling

Similarly to the aforementioned spectral representation (Krajník et al. 2014a), the proposed method still aims to identify the periodic patterns of the environment states and use them for predictions. Unlike the previous representation in (Krajník et al. 2014a), the method proposed here allows to update the underlying dynamic models incrementally from sparse, irregular observations. This method represents each state by the number of performed measurements n, its mean probability μ, and two sets $\mathcal{A}$, $\mathcal{B}$ of complex numbers α_k and β_k that correspond to the set Ω of periodicities ω_k that might be present in the modelled environment. Initially, the mean value μ is set to 0.5 and all α_k,β_k are set to 0, which corresponds to a completely unknown state.

Addition of a new measurement

Each time a state $s(t)$ is observed at time t, its representation is updated, i.e. the number of measurements n, the mean μ and values of $\mathcal{A}$, $\mathcal{B}$, which are actually a sparse spectral representation of $s(t)$, as follows:

$$\begin{aligned}
\mu &\leftarrow \tfrac{1}{n+1}\,(\, n\mu + s(t)\,), \\
\alpha_k &\leftarrow \tfrac{1}{n+1}\,(\, n\alpha_k + s(t)e^{-jt\omega_k}\,) \qquad \forall\, \omega_k \in \Omega, \\
\beta_k &\leftarrow \tfrac{1}{n+1}\,(\, n\beta_k + \mu e^{-jt\omega_k}\,) \qquad \forall\, \omega_k \in \Omega, \\
n &\leftarrow n+1.
\end{aligned} \tag{3.4}$$

The proposed update step is analogous to incremental averaging – the absolute values of $|\alpha_k - \beta_k|$ actually correspond to the average influence of a periodic process (with a frequency of ω_k) on the values of $s(t)$. Note that the size of the representation of the state (i.e. the number of elements in $\mathcal{A}$, $\mathcal{B}$) is independent of the number of observations, which means that the memory requirements of the proposed representation do not grow over time. Note also that if the times of observations t and frequencies ω_k are equally spaced, i.e. $t = i\Delta_t$ and $\omega_k = i\Delta_\omega$, $i \in \mathbb{N}$, then (3.4) corresponds to the traditional DFT.

Performing predictions

To predict the value of state $s(t)$ for a future time t, a set $\mathcal{C}$ consisting of $\gamma_k = \alpha_k - \beta_k$ is first created and then sorted descendingly according to the absolute values $|\gamma_k|$. Then, the first m elements γ_l are extracted along with their corresponding frequencies ω_l and the state's probability over time calculated as follows:

$$p(t) = \varsigma(\mu + \sum_{l=1}^{m} |\gamma_l| cos(\omega_k t + \texttt{arg}(\gamma_l))), \tag{3.5}$$

where $\varsigma(.)$ ensures that $p(t) \in [0,1]$. The choice of m determines how many periodic processes are considered for prediction. Setting m too low would mean that might not include some environment processes that actually influence the state, while setting m too high might include components of $\mathcal{C}$ that are caused by sensor noise. An optimal value of m can be determined by a cross-validation scheme.

3.3 3D Spatio-temporal Representation

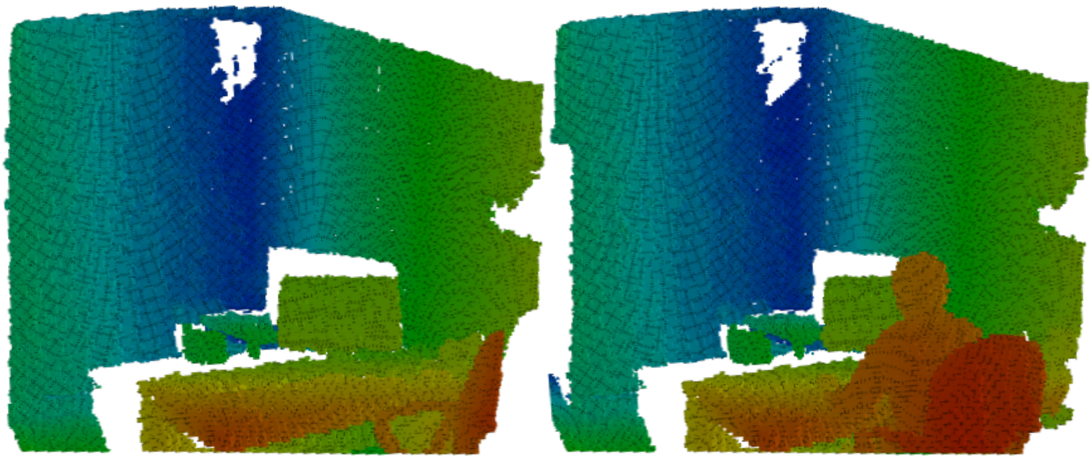
One of the goals of the proposed lifelong exploration strategy is to efficiently build, maintain and update a 3D spatio-temporal representation of the robot's operational environment. Thus, a method that enables efficient volumetric representation of dynamic three-dimensional environments over long periods of time is proposed and evaluated in this section. While the previous model description aimed at understanding how to model the environment changes based on their frequency analysis, its extension to 3D requires a study on the computational power and memory requirements.

One of the most popular environment representations is the occupancy grid, which allows for efficient probabilistic sensor fusion, motion planning, localisation and exploration. The main drawback of occupancy grids is their low-memory efficiency because they represent large, empty areas of the environment by a large amount of empty cells. This is mitigated by the so-called Octomap (Hornung et al. 2013) framework that locally adapts the grid resolution to the level of detail required. Octomaps have shown to be able to represent large-scale environments with a fine level of detail on standard computational hardware. The combination of FreMEn with the volumetric environment model called Octomap results in an environment model, where the occupancy of each cell (voxel) is a binary function of time, i.e. the occupancy of i^{th} cell is represented as $s_i(t)$. Thus, the efficiency of Octomaps to model large spatial scales and the efficiency of FreMEn to represent long periods of the time are combined in an efficient spatio-temporal environment model.

3D FreMEn-based Occupancy Grid

The occupancy of each cell (voxel) stored in an Octomap is considered to be a binary function of time, i.e. the occupancy of i^{th} cell is represented as $s_i(t)$. Thus, this approach takes a series of Octomaps observed over time and builds a temporal model of each observed voxel. After that, the system allows to calculate the state of the individual voxels and recover the Octomap for any given time.

To evaluate the ability of the uniform FreMEn method to represent the long-term dynamics of three-dimensional environments, two million occupancy grids of a university office were collected over the course of 112 days. The environment consisted of personal office with a working desk and meeting table. This dataset was collected by a stationary RGB-D camera that captured and stored a depth image every five seconds. These range measurements were integrated into a FreMEn occupancy grid, where the occupancy of each cell was modelled by the proposed method. Fine-grained occupancy grids captured by the RGB-D camera are shown in Figure 3.4 (for the purpose of visualization, the resolution of the grids shown is higher than those in the dataset). Each day, the spectral model



(a) *Empty office 3D grid.* ***(b)*** *Occupied office 3D grid.*

Figure 3.4: *Fine-grained 3D occupancy grids of the 'Office' dataset.*

of the entire grid was updated and the resulting representations were saved in separate files. To evaluate the efficiency of the resulting 4D representations, the compression ratios, estimation precisions, and times needed to calculate the update were measured.

The compression ratio evaluation was based on the size of the file that contains the spectral model. Assuming that a file of size z[bits] contains a FreMEn model of an environment with n states and m observations, and that a traditional model would use one bit per observation, the compression ratio is simply:

$$r = \frac{mn}{z}. \tag{3.6}$$

The compression ratios were calculated simply by comparing the size of the saved files to the theoretical size of a traditional model by Equation 3.6, where the number of modelled states n, i.e. the number of cells in the grid was ~213 000 and 17 200 observations per day, were considered. This means that storing all the observed states would require

∼500MB per day and a naive representation of the entire dataset would require around 50 GB of storage space. The estimation error of the entire model was calculated as an average of estimation errors of the individual cells that changed at least once – calculating the average estimation error for all cells would result in small numbers, because most of the cells represent space that is always empty. Finally, the update time was obtained by direct measurement of the time needed to update the spectral models of all the grid cells. These experiments were performed on an i7-4500U processor with 16 GB of RAM.

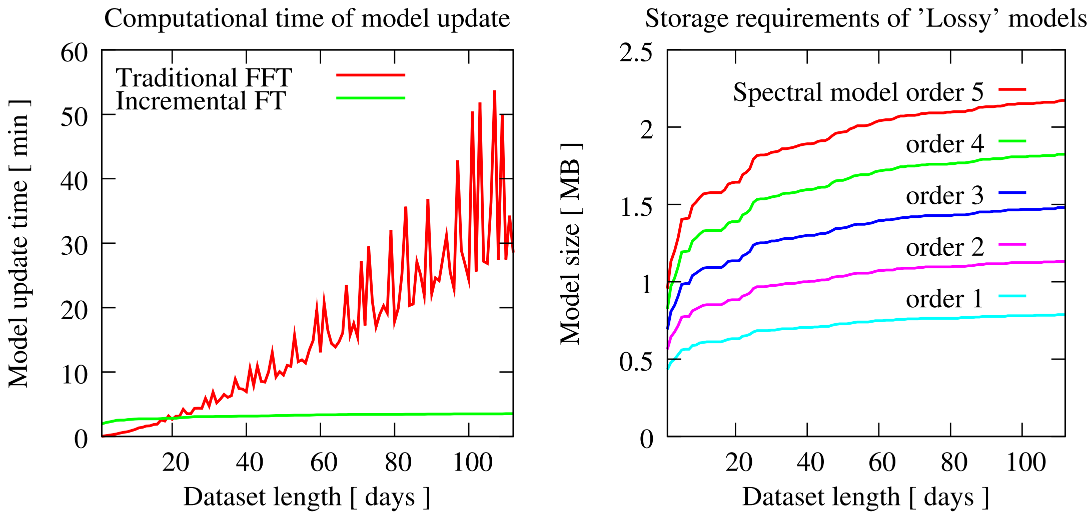


Figure 3.5: *Computational and memory requirements of the FreMEn spatio-temporal occupancy grids.*

Five types of spectral models were calculated. The first, 'lossless' model maintains not only the spectral representation, but also an outlier set $\mathcal{O}$ of each cell, and can recover all the measurements. The other, 'lossy - order 1-5' models did not use the outlier set and maintained 1 to 5 spectral components of the dynamic cells. The dependencies of the sizes of the 'lossy' models on the length of the dataset represented are shown in Figure 3.5. One can see that after some initial growth, the storage requirements of the models stabilize at the order of megabytes. The growth of the 'lossy' models is caused by the fact that longer data collection means that more cells change their states at least once, which causes the method to extend their temporal models.

Given that the naive representation of the dataset grows by 500 MB per day, the compression rates of the 'lossy' models actually grow in time (see Figure 3.6) and are in orders of 10 000. The 'lossless' representation grows linearly with time at a rate of 2 MB per day achieving compression rates of 1:250. Figure 3.5 also shows that the time needed to update the model, which represents 4×10^{11} cell observations is reasonably short – creation of a 16-week-long spatio-temporal model takes less than one hour. Using the non-uniform, incremental Fourier Transform results in an update time that exhibits a similar trend to the 'lossy' model sizes. This is caused by the fact that the number of cells for which the transform has to be calculated increases over time, i.e. the same effect that causes the growth of the 'lossy' models. Finally, the estimation errors of the spatio-temporal models

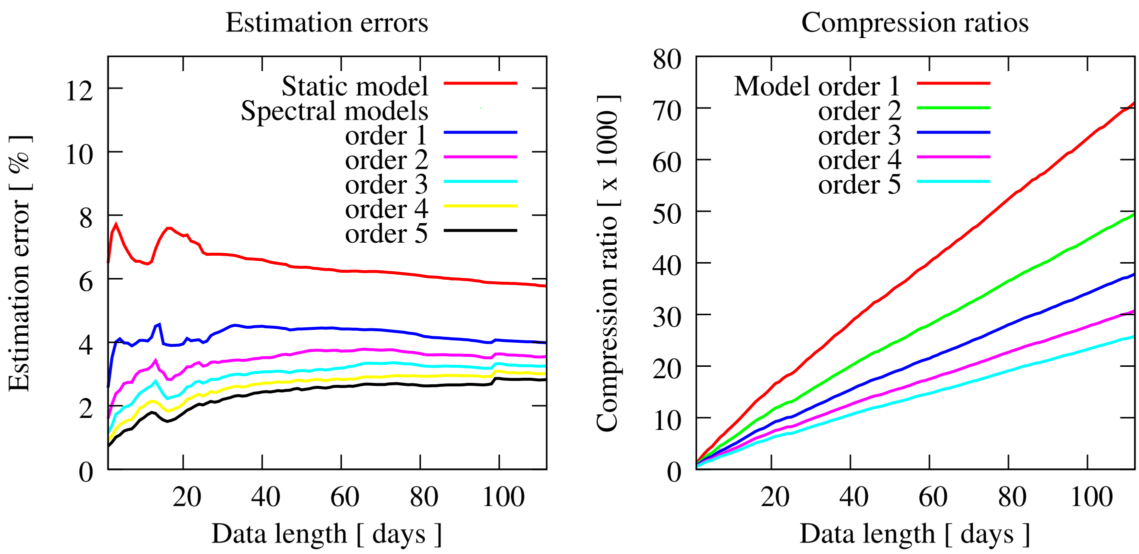


Figure 3.6: *Estimation errors and compression ratios of the FreMEn spatio-temporal occupancy grids.*

with different orders are presented in Figure 3.6, which shows that as the model includes more spectral components, its estimation error and compression rates drop. The 'Static' model, which takes into account all the observations and calculates the probability of a given state simply as the arithmetic mean of all its past observations, fails to correctly estimate approximately 6% of the states, while the 'lossy' FreMEn estimates fail in 3% to 4% cases. This means that using the FreMEn method reduces the amount of incorrectly estimated states by 30%-50%. Using the lossless method results in faithful (0% error) state reconstruction at the expense of a lower (1:250) compression rate. However, the number of observations per day performed in these experiments is excessive when using this approach in service mobile robots. In fact, the model error can be decreased by carefully selecting the times of observation and thus the need to develop novel strategies that allow to build and update spatio-temporal models. The results indicate that representing an increased rate of the environment changes would impact the error rate of the 'Static' model more than the FreMEn one. Also, an environment poor in periodicities would lead to similar performance between the 'Static' and the FreMEn models.

3.4 Information Metrics for Mobile Robotic Exploration

In Chapter 2, a review of exploration strategies for mobile robots was presented. In this review, the different strategies were categorised based on their planning approaches. Some of these strategies were based on information theoretic metrics in order to plan where in the environment to observe next. These family of strategies enabled the development of the lifelong exploration strategy described in this thesis and, consequently, a brief overview on information theory is required in order to understand the "mechanics" of the proposed strategy.

3.4.1 Information and Entropy: the basics

The definition of entropy in information theory was firstly introduced by Shannon (1948) and arose from the need to quantify information exchanged in distributed systems. While there is no universal and acknowledged definition of information, its definition is related to the concept of data. Data can be seen as the most basic building block in information theory. It consists of a set of symbols or facts. On the other hand, information is built upon these facts and provides a semantic meaning or context. Looking at the example of two agents continuously exchanging messages, even if the amount of data in the messages is constant (the message size does not change over time), the information encoded in the message might change, providing more or less information. Cuff (2016) states that "the more surprise we experience upon observing a particular outcome, the more information provided by that outcome", which is quantified by Shannon's entropy definition and fits perfectly in mobile robotic exploration.

For the case of mobile robotic exploration, and assuming the robot's operational environment is represented by an occupancy grid, each cell can be either occupied or free, and thereby only one bit is required to encode all the information. The Shannon's entropy is calculated using Equation 3.7.

$$H_j = -p_j \log_2(p_j) \quad [bit] \tag{3.7}$$

Taking into account that being occupied or free are mutually exclusive events, i.e. $p_{occ} = 1 - p_{free}$ and $p_{free} = 1 - p_{occ}$, the calculation of the entropy for the j^{th} cell in the grid is as follows:

$$H_j = -p_j \log_2(p_j) - (1 - p_j) \log_2(1 - p_j) \quad [bit] \tag{3.8}$$

As the probability of a cell being occupied is close to 0 or 1, the entropy $H(p)$ tends to zero, as shown in Figure 3.7. Thus, the observation of a fully explored location by the robot will result in no surprise and likewise the robot does not receive any information. On the other hand, if the mobile robot observes an unexplored area ($p = 0.5$), the robot receives 1 bit of information for each unknown cell observed.

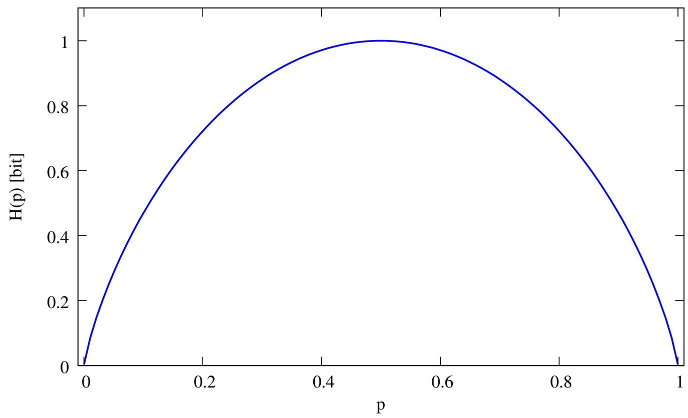


Figure 3.7: *Entropy evolution according to the proability of occupancy in a cell.*

3.4.2 Entropy Over Time

The above example was taking into account that the environment representation does not consider the temporal aspects, thereby, the occupancy of the cell does not change over time. However, the FreMEn model, described in Section 3.2.2 allows to have probabilistic functions of time that can be easily combined with the concept of entropy. Equations (3.3) and (3.5) allow to calculate the probability of occupancy of the i^{th} grid cell. Given that a robot placed at a particular location can observe a set $\mathcal{C}$ of the grid cells and the observation will cause the probability of these cells to approach either 0 or 1, the overall entropy reduction due to that particular observation can be calculated as

$$H(\mathcal{C}, t) = -\sum_{c_i \in \mathcal{C}} p(t) \log_2 p(t)[bit], \tag{3.9}$$

which corresponds to the expected information gained by observing a set of cells $\mathcal{C}$ at a time t.

The information-gain strategies take into account the experiences the robot has gathered so far to plan when and which location to visit. These strategies attempt to reduce the uncertainty of the environment models by planning the observations that maximize the potential information gain, assuming that direct observation of particular states at a given time reduces the entropy of these states to zero. Thus, the information gained by the observation of a particular location $\mathcal{L}$ at a time t can be estimated as the sum of the entropies of the states observed at a given location as

$$I(\mathcal{L}, t) = -\sum_{i \in \mathcal{L}} (p_i(t) log_2(p_i(t)) + (1 - p_i(t)) log_2(1 - p_i(t))). \tag{3.10}$$

3.5 Summary

In this chapter, the foundations and tools on which the main contributions of this thesis are built were introduced. The FreMEn model enables the representation of the environment states over time. This enables the efficient storage of previous observations, the representation of environment states as probabilistic functions of time and prediction of these states for a given time in the future. Moreover, the combination of the FreMEn model with a 3D representations was presented and a study that evaluates its computational and memory requirements using long-term datasets was conducted. Finally, the main concepts behind information theoretic exploration strategies were described and linked to the aforementioned spatio-temporal model.

To sum up, this chapter provides the theoretical background that enabled the development of a lifelong exploration strategy for mobile robots in changing environments, which is described in more detail in Chapters 5 and 6.

4

Benchmarking Long-term Robot Behaviours

While the previous chapter described the underlying methods of the exploration strategy proposed in this thesis, the current chapter focuses on the tools that enable its evaluation and comparison with other strategies.

Over the past years, the number of service mobile robots being deployed in real world scenarios has increased significantly. However, as stated in Chapter 1, long-term deployment of these service robots has led to the necessity of developing novel strategies that are able to deal with the environment changes and the consequent uncertainty. Thus, the field of long-term autonomy has been focusing on novel 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, as reviewed in Chapter 2. The outcome of these strategies is typically an environment representation that not only takes into account the spatial configuration of the world but also the way the environment states change over time. While the literature is rich in benchmarking methodologies for approaches that assume the environment to be static, the evaluation of lifelong learning strategies such as the one proposed in this thesis is still an open question. Typically, such benchmarking strategies are built upon datasets in which the sensory data is recorded by a robot with fixed behaviour (Howard & Roy 2003) and, consequently, the same sequence of perceptions are fed into the algorithms. However, in the case of mobile robot exploration strategies, the robot's behaviour cannot be evaluated online or it needs to be changed so it works with pre-recorded datasets. Additionally, these datasets do not include or consider the environment states that are not covered by the robot's field of view when making new observations. In the case one needs to evaluate robot behaviour, then a high fidelity simulation is needed. Furthermore, in the case of lifelong learning strategies, the simulator must be able to simulate changes, since the environment states highly influence the robot's decision making process. Thus, while datasets are typically suitable for benchmarking localisation and mapping algorithms, simulators enable the benchmarking of robot behaviour, such as navigation and exploration. Following this line of thought, to benchmark lifelong approaches, in which the robot's behaviour plays a key role, realistic dynamic simulation frameworks are required.

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 to replicate. For example, to ensure the same conditions for all teams in the 2014 Kinect Autonomous Mobile Robot Navigation Contest (Microsoft 2014), 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 in itself a very costly exercise.

4.1 Proposed Method

To address the aforementioned issues, a benchmarking approach based on recorded long-term datasets comprising high-level tracks of dynamic entities such as people, furniture and other objects of interest is described in this chapter. Thus, the main difference between the proposed datasets and the ones typically used for benchmarking is the “point of view”, i.e., the datasets described in this chapter provide a complete overview of the environment over time rather than having the sensory data recorded from the robot’s perspective only. These datasets were captured using an additional sensor system composed of ambient person-presence sensors (Fernandez-Carmona & Bellotto 2016) or hand-annotated images from overhead fisheye cameras.

Moreover, they can be used either directly or by means of a 3D simulation framework. High-level information about the changes in the environment can be given to the robot directly through a virtual sensor, which allows to eliminate the influence of the perception and localisation subsystems and focus on higher level planning. For example, Santos et al. (2016) uses a virtual sensor that can detect a human in a given room with 100% accuracy. However, the perception, localisation and navigation subsystems affect the way the exploration system works, so a simulator that can use the semantic information about the environment dynamics to generate a full 3D scene using geometric models of the dynamic objects is necessary.

Also, since this data is somehow pre-processed, using the datasets directly allows to benchmark only the lifelong decision-making strategy. On the other hand, the simulation uses the aforementioned semantic information tracks based on real sensory data 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 human spatio-temporal behaviour based on real-life dynamics rather than artificially generated dynamics, making the simulation a more accurate tool to compare different methods. Moreover, the full 3D simulation enables the evaluation of all the modules that constitute an intelligent autonomous system such as the navigation algorithms, which require decision-making and control of the robot, exploration or path planning, as well as state estimation algorithms, such as 3D mapping and self-localisation.

4.2 Datasets

To evaluate the ability of the various temporal models and exploration strategies, three datasets gathered over several weeks are proposed. The first, "Aruba" dataset was gathered by a team at the Center for Advanced Studies in Adaptive Systems (CASAS) to support their research concerning smart environments (Cook 2010). The second, "Brayford" dataset was created at the Lincoln Centre for Autonomous Systems (L-CAS) for their research on long-term mobile robot autonomy (Krajník et al. 2014b). Finally, the "Witham Wharf" was also recorded at L-CAS specifically to validate mapping strategies in changing environments. The aforementioned datasets were processed so that the dynamics of these environments are represented as visual-feature-based, semantic, topological and metric maps (Krajník et al. 2016).

4.2.1 Aruba

The 'Aruba' dataset consists of maps capturing 16-week long dynamics of a large apartment that was occupied by a single house-bound person who occasionally received visitors. An occupancy grid and a topological map were created for every minute of the 16-week long period – the resulting dataset contains over 160 000 metric and topological maps. Since the original dataset (Cook 2010) is simply a year-long collection of measurements from 50 different sensors spread over an eight-room apartment, these maps had to be created by means of simulation.

First, the events from the original datasets motion detectors were processed in order to establish the location of the people in the flat for every minute of the 16 weeks. Then, the flat was partitioned into ten different areas, where eight areas represent the rooms and one corresponds to a corridor. Then a topological map that indicates the presence of people in these locations was created as shown in Figure 4.1.

To obtain the metric representation, a simulated environment with the same structure as the "CASAS" apartment was created, see Figure 4.2. Then the simulation was provided

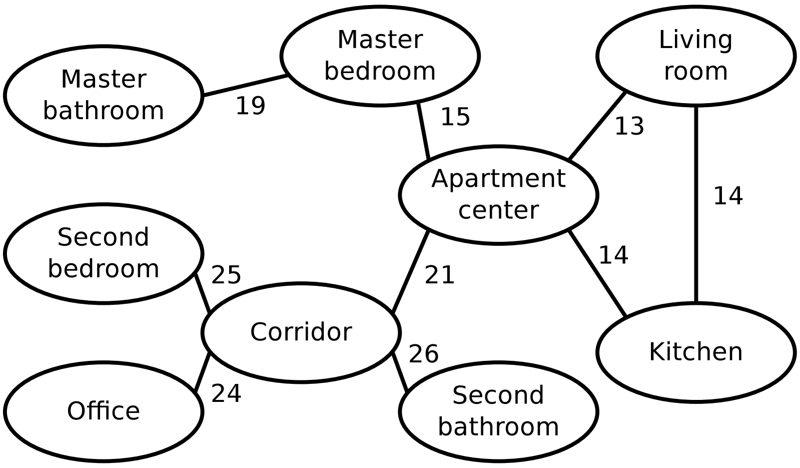


Figure 4.1: *The Aruba dataset topological map.*

with a sequence of person locations recovered in the previous step. As a result, the simulated environment contains physical models of people at locations provided by the real-world dataset, and thus it reflects the dynamics of the real apartment. A virtual RGB-D camera equipped robot was also introduced into the virtual environment. Every time the configuration of the simulated environment (i.e. locations of the people) changed, the robot used its 3D sensors to create occupancy grids of the flat's individual rooms. Thus, occupancy grids that reflect the real environment dynamics minute-by-minute were obtained for 16 weeks.

Figure 4.2: *The Aruba 3D enviornment.*

4.2.2 Brayford

The Brayford dataset was originally collected for the purpose of benchmarking long-term mobile robot localization algorithms in dynamic environments (Krajník et al. 2014b). The data collection was performed by a MetraLabs Scitos G5 robot equipped with an RGB-D camera in a large, open-space office of the Lincoln Centre for Autonomous Systems. The robot was set up to obtain RGB-D images of eight designated areas every 10 minutes for a period of one week. Representative examples of the captured images are shown in Figures 4.3. While the high-level environment model of this dataset contains informa-

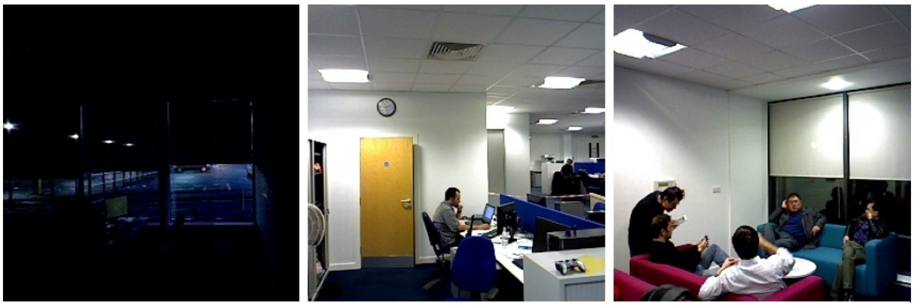
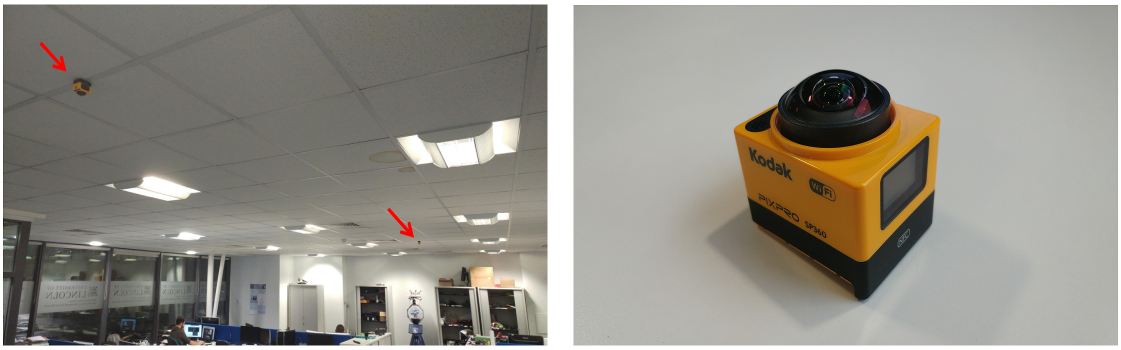


Figure 4.3: *Examples of Brayford dataset images.*

tion about people presence at the individual locations, the states of the low-level model represent the visibilities of image features. The resulting dataset contains more than 8000 feature-based and 8000 semantic maps collected over a period of one week (Krajnk et al. 2017).

4.2.3 Witham Wharf

The "Witham Wharf" 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, as shown in Figure 4.4, which took a snapshot of the environment every second over 5 business days. The dataset consists of a log file containing the positions of several dynamic objects over time, which were obtained by manually annotating the successive snapshots taken by the cameras. The objects' positions were acquired from videos recorded by two ceiling cameras, as shown in Figure 4.5.



(a) Placement of the fisheye cameras in the environment.

(b) The Kodak PixPro SP360 camera used.

Figure 4.4: *Setup used to record the "Witham Wharf" dataset.*

Figure 4.5: *View from one of the cameras installed in the L-CAS office.*

4.3 Simulation Environments

The proposed benchmarking approach for lifelong strategies 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 has been captured by physical sensors installed in a real environment.

The simulation environment was based on MORSE (Echeverria et al. 2011), which is part of the STRANDS project software (Hawes et al. 2016). However, any other 3D simulation environment could be used, such as Gazebo. A 3D replica of the environment was first created, see Figure 4.6. This replica was based on the office plans and the current furniture arrangement. Several dynamic objects were then added, such as chairs, laptops and humans.

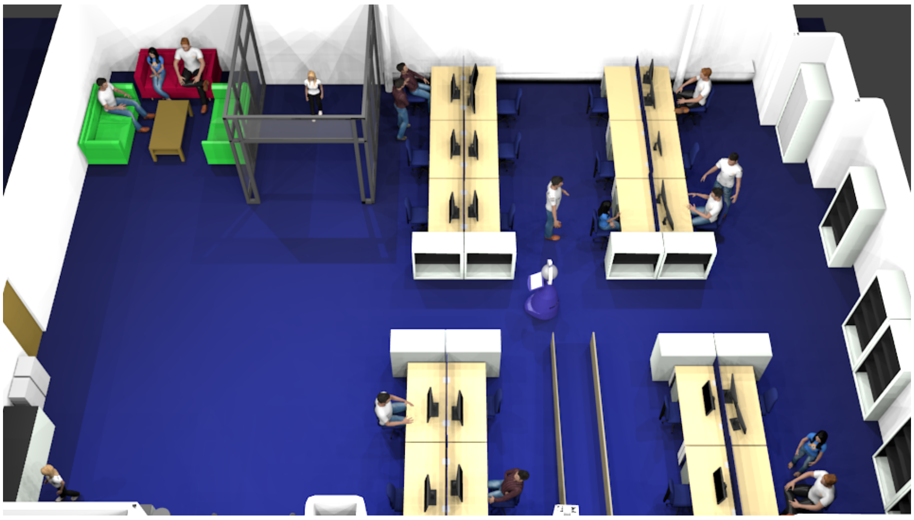


Figure 4.6: *Simulated environment for the "Witham Wharf" dataset.*

The configuration module controls the simulation by maintaining a list of all entities and their positions in the environment, rearranging them in the environment according to 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. Moreover, a software component that allows to reconfigure the simulated environment on the fly was created. Combination of the reconfigurable simulator with the aforementioned datasets allows to create a realistic simulation that reflects the real-world dynamics. Thus, this simulation does not only reflect the environment static structure but also simulates dynamic elements, such as moving people, chairs, laptops and doors (see Figure 4.6).

The main advantage of the simulation is the possibility to obtain ground truth that spans the entire space and time of the experiment. The ground truth for a single time slot was obtained by configuring the simulation for a particular time and letting the robot perform its 3D sweeps at several locations in order to obtain a complete overview of the environment, as shown in Figure 4.7. This tool is available for download at `https://github.com/santosj/lifelong_benchmarking`.

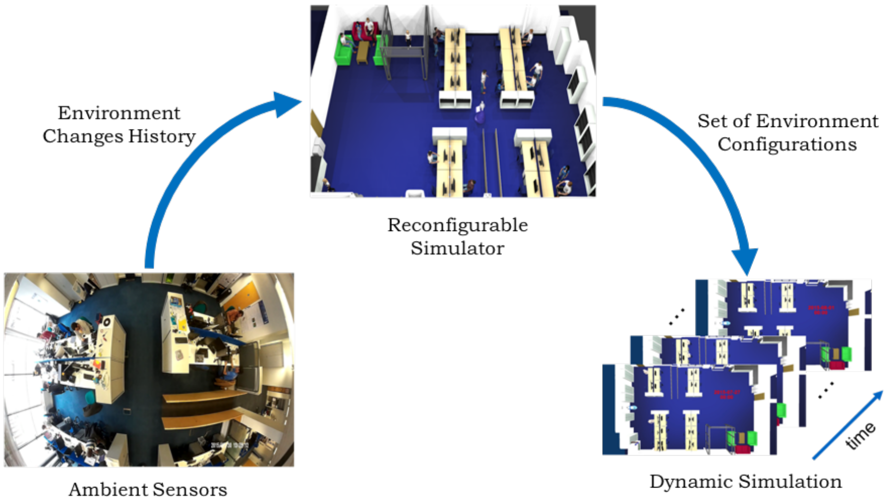


Figure 4.7: *Simulation overview. Each entry in the dataset corresponds to a given re-arrangement of all objects and human models in the environment.*

4.4 Summary

This chapter described a method that allows to benchmark spatio-temporal strategies in long-term deployments. The described framework has been used on 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. Moreover, additional datasets and 3D environments can be easily added to the current framework and used to benchmark lifelong learning strategies in different types of environments.

This benchmarking framework played a key role in the development of the lifelong exploration strategy proposed in this thesis. More details on the experimental validation of this strategy are provided in Chapters 5 and 6.

5

Exploration Strategies for Long-term Deployments

As stated previously, mobile service robots have to cope with environmental changes in order to operate safely and robustly in human-populated environments. Also, the majority of mobile robot mapping approaches are built upon the assumption that the world is static, and thus do not take into account the need to re-observe the environment and update the world model when deployed over long periods of time. In Section 2.2, several approaches that cope with changing environments were described, although the mobile robot does not actively decide how to build and maintain the world model. In fact, these approaches are typically validated using pre-recorded datasets, ignoring the impact of a decision-making on the world model quality and the ability to use the model to improve the robot's long-term performance.

The primary goal of the lifelong exploration strategy proposed in this thesis is to build, update and maintain a 3D spatio-temporal representation of the robot's operational environment, or, in other words, a 4D model of the world, while taking into account the time constraints that arise from the robot's daily duties. While the introduction of spatio-temporal world models enables the robot to learn about the environment changes, strategies to efficiently and intelligently build and maintain these models are also required.

As seen in Section 2.1, classic exploration strategies aim at building a spatial model that covers the robot's entire operational environment, ignoring the fact the environment might change after its completion. However, in order to keep the 4D representation up to date, an exploration strategy has to reason about the times and become a never-ending exploration task for the following reasons. Firstly, some areas of the operational environment are not exactly predictable during certain times, which requires the robot to re-observe those locations at the times when their state is uncertain. For example, even if the general habits of a certain person are known, his/her presence at his/her workplace is uncertain around the start and end of office hours, and thus, it makes sense to observe the workplace during these times to further improve the 4D representation. Secondly, the patterns in the environment dynamics might change and identification of new patterns requires re-observation of the particular area at the right times. For example, the workplace might later be occupied by a new employee with a different working pattern. Additionally, the general structure of the environment can change due to reconstruction or displacement of furniture.

Thus, the robot needs to take repeated observations of locations in its operational environment over time in order to successfully build and maintain a spatio-temporal model. This requires the robot to continuously explore the environment in addition to the other tasks it was designed for. Therefore, lifelong exploration must become a part of the robot's daily routine that has to be carried out along with other tasks that the robot is required to perform. The ability to build and maintain the aforementioned 4D representation allows the mobile robot to better cope with changes in the environment and to perform its daily duties efficiently. Hence, being able to build, maintain and reason over such an environment representation plays a key role in achieving long-term operation without requiring any major human intervention, i.e., long-term autonomy.

To further understand the requirements and challenges of a lifelong exploration strategy that efficiently maintains a 4D world model, which accurately represents the environment, a study on different spatio-temporal representations and exploration strategies must be conducted. For this reason, before moving to a fully metric spatio-temporal representation, one has to know which strategies and models are more suitable for lifelong exploration of changing environments. In order to efficiently understand the impact of the different constraints and further understand the challenges of building and maintaining spatio-temporal representations, one has to reduce the complexity of the problem. Thus, in this chapter an investigation using high-level data representations is carried out. Additionally, the investigation conducted considers the mobile robot not only to have noise-free sensors but also to know the topology of the environment *a priori*. Then, an evaluation of all possible combinations of four different spatio-temporal models and five planning strategies by their long-term performance, according to their ability to provide an accurate environment model over time, is conducted. To complete this study, the exploration versus exploitation dilemma is re-visited, and the impact of different exploration ratios on the overall accuracy of the model is evaluated.

To sum up, this chapter presents a detailed description of the concept of lifelong exploration as well as a study on a higher layer of abstraction in order to fully understand how to achieve a 4D lifelong exploratory behaviour. This study has been presented in (Santos et al. 2016, Krajník et al. 2015c).

5.0.1 Notation

The notation used over the following sections to define the problem of lifelong exploration and the models used are as follows:

- $\mathcal{S}$ denotes the set of world states;
- $\mathcal{L}$ denotes the set of locations to explore;
- l location to explore;
- ϵ denotes the model error;
- μ denotes the mean probability;
- $\mathcal{T}$ denotes the set of time slots to perform exploration;
- λ denotes the event rate;
- I denotes the information-gain.

5.1 Problem Definition

The primary purpose of robotic exploration is to autonomously acquire a complete and precise model of the robot's operational environment. To explore efficiently, the robot has to direct its attention to environment areas that are currently unknown. If the world was static, these areas would simply correspond to previously unvisited locations. In the case of dynamic environments, visiting all locations only once is not enough, because they may change over time. Thus, dynamic exploration requires that the environment locations are revisited and their re-observations are used to update a dynamic environment model. However, revisiting the individual locations with the same frequency and on a regular basis is not efficient because the environment dynamics will, in general, not be homogeneous (i.e. certain areas may change more often and the changes occur only at certain times). Similarly to the static environment exploration problem, the robot should revisit only the areas states of which are unknown at the time of the planned visits. Thus, the robot has to use its environment model to predict the uncertainty of the individual locations over time and use these predictions to plan observations that improve its knowledge about the world's dynamics.

To tackle the problem of predicting environment uncertainty over time, the FreMEn model described in Section 3.2.3 is used to model the probabilities and entropies of the environment states as functions of time, as described in Section 3.4. Unlike the method in (Krajník et al. 2014b) that requires frequent and regular environment observations, the method proposed in this chapter allows to incrementally and continuously update the spatio-temporal model from sparse observations taken at different locations and times. This eliminates the need for a separate training and deployment phase and allows integration of spatio-temporal exploration into the robot's daily routine. Thus, the robot can continuously refine its internal environment model and improve its efficiency from the experience gathered over long periods of time.

5.1.1 Problem definition

Let us represent the environment as a set $\mathcal{S}$ of n discrete non-stationary independent binary states $s_i(t)$ that are observable by a mobile robot through its sensors. The states $s_i(t)$ might represent the occupancy of individual cells in an occupancy grid, the traversability of edges in a topological map, the visibility of environmental features, etc. Since these states are dynamic and the robot cannot observe all the states all the time, it maintains an internal environment model that is denoted as a set $\mathcal{S}'$, where each element $s'_i(t)$ corresponds to the real-world state $s_i(t)$. To represent the fact that the currently unobserved states are uncertain, each state is associated with a probability value $p_i(t)$ such that $p_i(t) = P(s_i(t) = 1)$. The probability function $p_i(t)$ and the way it is calculated from the past observations of $s_i(t)$ is referred as **temporal model**.

Let us define a **location** as a set of environment states that can be observed simultaneously, i.e. a location $\mathcal{L}_j$ is a subset of $\mathcal{S}$, such that by visiting location $\mathcal{L}_j$ at time t, observations of the states that belong to $\mathcal{L}_j$ are obtained. Given that the robot location at time t is $l(t)$, the robot can directly observe only the states s_i of location $\mathcal{L}_{l(t)}$ and the states observable at other locations have to be estimated. Thus, the states of the robot's internal environment model are

$$s'_i(t) = \begin{matrix} s_i(t) & \text{if } s_i \in \mathcal{L}_{l(t)} \\ p_i(t) \geq 0.5 & \text{otherwise.} \end{matrix} \tag{5.1}$$

The purpose of the exploration process is to obtain and maintain as faithful an environment model as possible, i.e. to minimize the difference between the states of the real environment $\mathcal{S}$ and its model $\mathcal{S}'$. Technically, this corresponds to minimization of the model error $\epsilon(T)$ calculated as the difference between the real and estimated states over the time period $[0, T)$ as

$$\epsilon(T) = \frac{1}{T} \sum_{t=0}^{T-1} \sum_{i=1}^{n} |s'_i(t) - s_i(t)|. \tag{5.2}$$

Although the reduction of the error $\epsilon(T)$ can be partially achieved by visiting the relevant locations as often as possible, the robot has to perform other tasks and the number of observations is typically limited. Thus, the robot has to carefully plan where and when to perform observations so that it obtains the relevant data to create, maintain and refine its spatio-temporal models of the environment. From a technical point of view, the robot has to use its internal temporal models $p_i(t)$ to determine a sequence of locations $l(t)$. The way the robot plans the sequence of $l(t)$ from $p_i(t)$ is referred to as its **exploration strategy**.

5.2 Alternative Models

The most popular way to deal with the uncertainty of the environment is based on Bayesian filtering, which updates the state estimates based on the sensor noise characteristics (Thrun et al. 2005). The typical measurement rate of the robot sensors exceeds the mid- to long-term environment dynamics, therefore the Bayesian update scheme causes the probabilities of the observed states to quickly converge towards the latest observed values. Thus, the traditional Bayesian filtering tends to reflect the latest state measurements and acts as a **Short-term Memory (SM)**. Typically, the traditional environment representations tend to reflect the latest state measurements, discarding older measurements. However, for long-term deployment it is sensible to use representations that somehow reflect the prior environment states since the initial deployment stage. To strengthen this study, two additional environment representations that take into account all the previous observations are described in this section, a **Long-term Memory (LM)** model and **Gaussian Mixture Models (GMM)**. However, these models are not contributions of this thesis, but rather state-of-the-art world representations used to complete and strengthen the study conducted in this chapter.

5.2.1 Short-term Memory

In order to model the short-term dynamics, a similar model to (Saarinen et al. 2012) is proposed. This model is based on a Markov chain and aims at representing not only the environment states but also how likely they will change given the last observed state and the time it was observed. Assuming that each measured state s can be occupied or free, the goal of this method is to estimate the conditional probabilities that represent the transition from a state to another, which are $p(s=0|s=1)$ and $p(s=1|s=0)$. These probabilities are estimated by means of a Poisson process, i.e., these probabilities can be approximated by the ratio between the number of state changes observed and the total number of observations.

$$\begin{aligned} p(s=0|s=1) &\approx \lambda_0 = \tfrac{\#nr\ exit\ events+1}{\#nr\ observations} \\ p(s=1|s=0) &\approx \lambda_1 = \tfrac{\#nr\ entry\ events+1}{\#nr\ observations} \end{aligned} \tag{5.3}$$

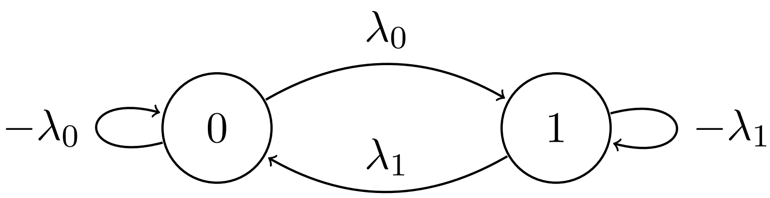


Figure 5.1: *The underlying Markov chain in the short-term memory model.*

However, as described in Section 5.1, due to the nature of spatio-temporal exploration, the observations of states are not performed uniformly in time, and consequently the discrete Markov chain described in (Saarinen et al. 2012) as well as the estimation of aforementioned probabilities do not apply in our case. Thus, a continuous Markov chain to model the recency of the environment states is proposed, as shown in Figure 5.1. In this case, the transition rates between the states 0 and 1, λ_0 and λ_1, are inversely proportional to the average time that an observed state remains at 0 or 1. From the Markov chain shown in Figure 5.1, it is possible to infer the transition rate matrix, Q, as follows:

$$Q = \begin{bmatrix} -\lambda_0 & \lambda_0 \\ \lambda_1 & -\lambda_1 \end{bmatrix}, \tag{5.4}$$

Thus, the probability vectors are given by:

$$\begin{aligned} \dot{p_0}(t) &= -\lambda_0 p_0 + \lambda_1 p_1(t) \\ \dot{p_1} &= -\lambda_1 p_1(t) + \lambda_0 p_0(t) \end{aligned} . \tag{5.5}$$

Since there are only two states, for any time t, we have $p_0(t) + p_1(t) = 1$. Thus, by differentiating and substituting the previous set of equations, Equation 5.6 is obtained, which allows to predict the probability of the state $s(t)$ for a given future time t, where T is the time of the most recent observation.

$$p(t) = \frac{\lambda_0}{\lambda_0 + \lambda_1} + (p(T) - \frac{\lambda_0}{\lambda_0 + \lambda_1})e^{-(\lambda_0+\lambda_1)(t-T)}. \tag{5.6}$$

5.2.2 Long-term Memory

A way to reflect the uncertainty of the observed states in the long-term is to implement a **Long-term Memory (LM)**. The proposed model works as a memory that takes into account all the observations and calculates the probability of a given state simply as the arithmetic mean of all its past observations.

5.2.3 Gaussian Mixture Models

Gaussian Mixture Models (GMM) that can approximate multi-dimensional functions as a weighted sum of Gaussian component densities are a well-established method of function approximation. GMMs find their applications in numerous fields ranging from botany to psychology (Titterington et al. 1985). The Gaussian Mixture Model of the function $f(t)$ is the weighted sum of m Gaussian functions:

$$f(t) = \frac{1}{\sqrt{2\pi}} \sum_{j=1}^{m} \frac{w_j}{\sigma_j} e^{-\frac{(t-\mu_j)^2}{2\sigma_j^2}}. \tag{5.7}$$

The parameters of individual components of GMMs, i.e. the weights w_k, means μ_j and variances σ_j are typically estimated from training data using the iterative Expectation Maximization (EM) or Maximum A-Posteriori (MAP) algorithms. While GMMs can model arbitrarily-shaped functions, their limitation rests in the fact that they cannot naturally represent functions that are periodic.

To deal with this issue, it is assumed that people perform most of their activities on a daily basis and thus the object presence in the individual areas is considered as being the same for every day. While this assumption is not entirely correct (as working days will be different from weekends), such a temporal model might still be better than a 'static' model where the probability of object presence is a constant.

Prior knowledge of the periodicity allows to transform the measured sequence of states $s(t)$ into a sequence $p'(t)$ by

$$p'(t) = \frac{k}{\tau} \sum_{i=1}^{k/\tau} s(t + i\tau), \tag{5.8}$$

where τ is the assumed period and k is the $s(t)$ sequence length. After calculating $p'(t)$, the Expectation Maximization algorithm to find the means μ_j, variances σ_j and weights w_j

of its Gaussian Mixture, approximation is employed. Thus, the probability of occupancy of a room at time t is given by

$$p(t) = \frac{1}{\sqrt{2\pi}} \sum_{j=1}^{m} \frac{w_j}{\sigma_j} e^{-\frac{(mod(t,\tau)-\mu_j)^2}{2\sigma_j^2}}, \tag{5.9}$$

where τ is the a priori known period of the function $p(t)$ and *mod* is a modulo operator. The advantages of this Periodic-GMM (PerGaM) are complementary to the weaknesses of the FFT-based one. It can approximate even short, multiple events, but it can represent only one period that has to be known a priori.

An example comparison of the GMM and FreMEn models of person presence in a week-long experiment in an office environment is shown in Figure 5.2. The figure demonstrates

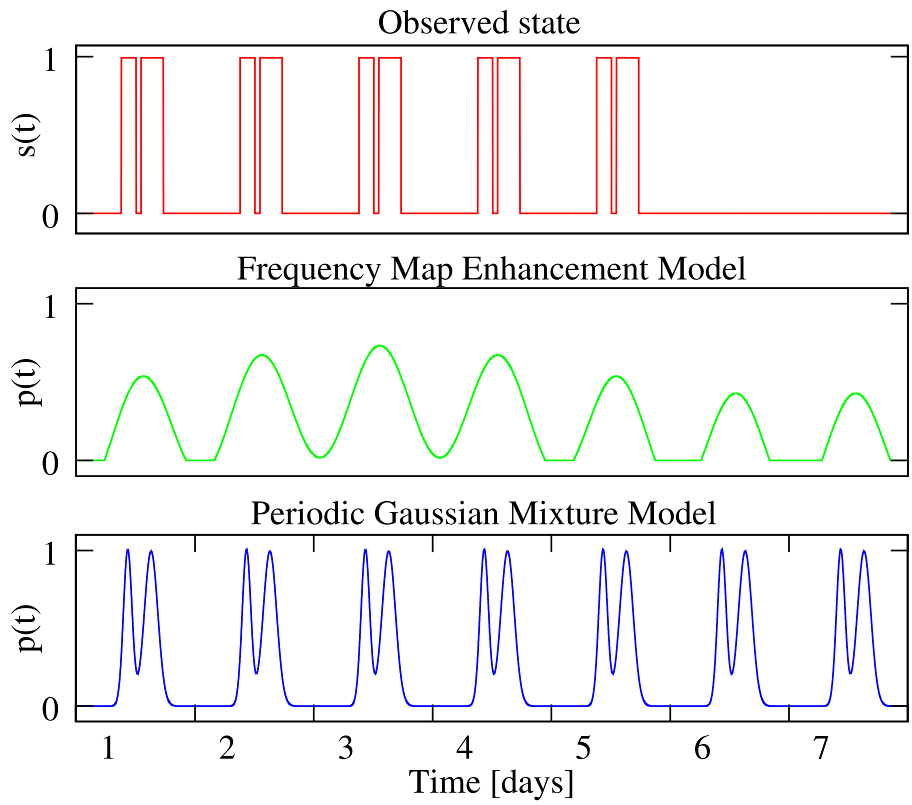


Figure 5.2: *PerGaM and FreMEn models example/comparison.*

that while GMM can model short-term event like lunch-breaks, it fails to capture the week-long dynamics.

5.3 Exploration Strategies

As noted in Section 5.1, an exploration strategy is defined as a process that determines both which locations to visit and when to visit them. One has to assume that a real mobile robot has to perform other tasks as well and can spend only a fraction of the total time on actual exploration. This fraction is referred to as the exploration ratio e, e.g. $e = 0.2$ means that the robot can spend 20% of its operational time on exploration.

Thus, given an exploration ratio e and a set $\mathcal{T}$ of time intervals $[t_s, t_{s+1})$, the exploration algorithm has to determine a sequence $l(t_s)$ of locations to visit. To represent situations where the time slot $[t_s, t_{s+1})$ is allocated to an unrelated activity, the value of $l(t_s)$ is set to zero, whereas a non-zero value of $l(t_s)$ signifies the location to be observed during $[t_s, t_{s+1})$.

5.3.1 Information-based Strategies

Information-gain strategies take into account the experiences the robot has gathered so far to plan when and which location to visit. These strategies attempt to reduce the uncertainty of the environment models by planning those observations that maximize the potential information-gain. To estimate how much information is gained by a particular observation, the definition of entropy is used as explained in Section 3.4. The direct observation of particular states at a given time is assumed to reduce the entropy of these states to zero. Thus, the information gained by a particular observation can be estimated as the sum of the entropies of the states observed at a given location as

$$I(\mathcal{L}, t) = -\sum_{i \in \mathcal{L}} (p_i(t) log_2(p_i(t)) + (1 - p_i(t)) log_2(1 - p_i(t))). \tag{5.10}$$

Greedy Strategy

The **Greedy** strategy calculates the potential information gains for all given time slots and locations, then assigns the best location to visit at each time slot. Then, it selects a subset $\mathcal{T}'$ of time slots with the highest information gain such that $e = |\mathcal{T}'|/|\mathcal{T}|$. The remaining time slots are assigned to other tasks. Thus, this strategy maximizes the potential information gain obtained over the time slots in the set $\mathcal{T}$.

Monte Carlo Strategy

The **Monte Carlo** strategy chooses the locations randomly, but the probability of selecting a given location at a given time is proportional to the estimated information gain. At first, it estimates the $I(l, t_s)$ for all given time slots and locations and sums these values to I'. Then, it calculates the value of $I(0, t_s) = I'(1-e)/(ne)$. Finally, it calculates the probabilities of each $l(t_s)$ as

$$P(l(t_s) = j) = \frac{I(j, t_s) + \iota}{\sum_{i \in \mathcal{L}} I(i, t_s) + \iota}. \tag{5.11}$$

Here, the value of $I(0, t_s)$ does not represent actual information gain but is added to ensure that the exploration ratio e is satisfied by ensuring sufficient chance of assigning the time slots to exploration-unrelated tasks. The positive constant ι ensures that the locations will be occasionally visited even at times when the spatio-temporal model predicts their state with absolute certainty. This allows the robot to detect unexpected changes in the environment dynamics.

Novelty-driven Strategy

The **Novelty-driven** strategy follows the same principle as the Monte Carlo one. However, unlike the Monte-Carlo strategy, which strictly follows a schedule determined by Equation 5.11, the novelty-driven strategy uses a combination of temporal models to identify situations where a change in the Monte-Carlo schedule would result in a large amount of information obtained. To identify such situations, the novelty-driven strategy predicts the amount of information obtainable in the following time slot by:

$$I(t) = -p_{expc}(t) log_2(p_{info}(t)) - (1 - p_{expc}(t)) log_2(1 - p_{info}(t)), \tag{5.12}$$

where $p_{expc}(t)$ is calculated by the short-term memory model (see Section 5.2.1) and serves as a measure of expectation, whereas p_{info} is provided by another model and represents the amount of information expected. If $I'(\mathcal{L}, t) >> I(\mathcal{L}, t)$, i.e. the amount of information predicted by Equation 5.12 is significantly higher than the value calculated by Equation 5.10, then the location to visit in the following time slot is changed accordingly. Thus, if the observed states at a recently visited location did not match their predictions, the robot re-observes the location again to obtain more information about this unexpected event.

5.3.2 Uninformed Strategies

For comparison purposes, strategies which select the places to visit regardless of the environment dynamics were considered. These strategies calculate the sequence of visits $l(t_s)$ simply from the values of the ratio e, number of locations n and number of time slots m.

Random Strategy

The probability of a given slot being assigned to a non-exploration task is equal to $1 - e$, and the probability of visiting the individual locations is uniform and equal to e/n.

5.3.3 Round Robin Strategy

The **Round-Robin** strategy visits all areas of the environment with the same frequency, interleaving the observations with other tasks so that the exploration ratio e is satisfied.

5.4 Qualitative Evaluation

To gain an insight into the robot's exploratory behaviour, we interpret the data gathered during the exploration of the 'Aruba' topological map as described in Section 4.2. Here, the robot's task was to create a spatio-temporal model of person presence in the individual rooms of a small apartment. For the purpose of this explanation, let us focus on the dynamics of three rooms only – the bedroom, the kitchen and the storage room. Let the robot use the best-performing exploration method that combines the FreMEn temporal models and the Monte Carlo exploration strategy. Applying the proposed spatio-temporal exploration method to this dataset produced the behaviour in Figure 5.3. The top part of Figure 5.3 shows the real state of the environment, where the three binary functions $s_i(t)$ represent the room's occupancies over time. The second part shows the robot's internal model of the environment, i.e. the probabilities $p_i(t)$. The third graph displays the information that is expected to be obtained by visiting these three locations at a given time. Finally, the bottom graph shows which locations have been visited at a particular time – an exploration ratio of $e = 0.5$ is assumed, which reflects the situation where the robot has to spend half of its time on its charging station. The color of the dots in bottom graph reflect the room visited, the horizontal position relates to the times of the visit and vertical placement reflects the outcome of the observation, i.e. person present or absent. To understand the robot behaviour, one should read the graphs from left to right: initially, the knowledge of the robot about the person presence is nil, but after each day, the probabilistic and entropy models are updated from the previous day observation, which is reflected by the observation schedule. The following description intends to shed some light on how the robot's understanding of the environment changes over time and how this affects its exploratory behaviour day by day. The complete overview of Figure 5.3 is shown in Appendix B.

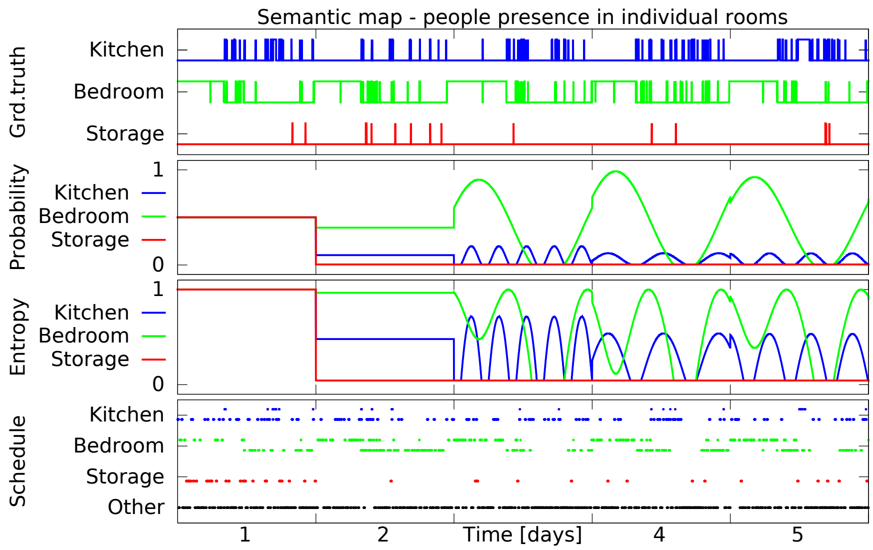


Figure 5.3: *Spatio-temporal exploration behaviour: The robot uses its probabilistic world model (second row) and spatio-temporal entropy estimates (third row) to schedule its observations (bottom graph) and learn the environment dynamics (top). As the environment knowledge improves over time, the scheduled observations provide more information which allows for further refinement of the environment model.*

Day one

Initially, the robot has no knowledge of the environment and therefore the probabilities $p_i(t)$ of the world states $s(t)$ are equal to 0.5. This means that the expected information gain from visiting any of the rooms equals 1 bit at any time of the first day. Thus, the robot has no room or time preference when scheduling the first day's observations, which results in scheduling of an equal amount of observations spread over the entire day and the three rooms.

Day two

After performing the first day's observations, the environment models provide enough evidence that the three rooms are not occupied with the same probability. This is reflected in the second day's environment model – see the probability functions $p_i(t)$ of the second day in Figure 5.3. Thus, the robot expects to gain more information by visiting the bedroom and kitchen than by going to the storage room. This is reflected in the second day's observation schedule – the last row of Figure 5.3 shows that the first two rooms are visited more often.

Day three

The additional observations obtained during the second day provide information about the rooms' dynamics: the robot assumes that the bedroom has a daily periodicity and that the kitchen is visited five times per day. This causes the expected information gain to be time-dependent – the third day of the third row of Figure 5.3 shows that evening and morning observations of the bedroom provide more information than in the afternoon. This fact is rather intuitive: visiting the room at the time of its state transition allows to refine the room's state periodicity. Thus, on the third day, the bedroom is visited mostly in the evening and morning, while the afternoon visits are scheduled to the kitchen.

Days four and five

Based on the data gathered during the third day, the robot modifies its hypothesis about the periodicity of activities in the kitchen and assumes that it is visited three times per day. During the following days, the robot tends to visit the kitchen and bedroom more often, and checks the storage room only occasionally. While the kitchen is visited mostly in the early afternoon, the bedroom is visited in late evenings and mornings, which allows to refine the robot's model of the person's daily habits.

This example indicates that the combination of a probabilistic temporal model with an information-based strategy not only allows the robot to obtain knowledge about the environment dynamics, but the observations are scheduled in a seemingly logical way: at first, all the locations are visited often and with the same frequency. As the spatio-temporal environment model becomes more refined, the robot tends to visit particular locations only at times when their states are uncertain.

While the robot exploration behaviour seems to be intelligent, the real question is how efficient the algorithm really is. As noted in Section 5.1, the efficiency of the exploration algorithm is evaluated by comparing the robot's internal model to the real environment state by Equation (5.2).

5.5 Experimental Evaluation

To evaluate the ability of the various temporal models and exploration strategies, a comparison using the 'Aruba' and 'Brayford' datasets described in Chapter 4.2 is performed in this section. For this purpose, it is assumed that the aforementioned datasets reflect the real state of the environments they have been captured in, and thus the sequence of the observations in the datasets are used as ground truth. To evaluate how the various temporal models and exploration strategies affect the robot's ability to create and update its internal environment models, the exploration process is emulated using these datasets. Also, it is assumed that the exploration can be performed during only half of the robot's operational time (i.e. $e = 0.5$), and that a single observation takes 10 minutes. While 10 minutes might seem like a long time, creation of a 3D occupancy grid of a given location means that the robot has to position itself precisely, and capture and process several RGB-D images. More precisely, similar to the MetraLabs Scitos G5 mobile robot used in the STRANDS project, the simulated mobile robot is equipped with a PTU unit that allows to capture a full view of the environment. Thus, taking into account the Field of View (FoV) of 58° horizontal and 45° vertical of the RGB-D camera used, approximately 50 RGB-D images from different viewpoints need to be captured. Additionally, several RGB-D images are taken per viewpoint and then averaged in order to deal with sensor noise.

This time also includes navigation to the given spot, leaving the charging station, etc.

This exploration procedure corresponds to the situation when the robot updates its spatio-temporal model and generates a new observation schedule every 24 hours at midnight. The robot starts with an empty environment model that has all probabilities constant and equal to 0.5.

First, the entropy functions of the individual locations are calculated and 72 observations for the following day are scheduled. Then, these 72 observations are retrieved from the given dataset and the temporal models of the environment states are updated. The updated temporal models are used to recalculate the spatio-temporal entropy and the next day's observation schedule is then generated. These steps are repeated for every day of the given dataset.

5.5.1 Evaluating environment model error

To compare the performance of the temporal models and exploration strategies described in Sections 5.2 and 5.3, the resulting world model is compared to the actual dataset using Equation 5.2, which estimates the error in the environment model. Since there are 4 temporal models and 5 exploration strategies, each comparison considers 20 values that characterize the ratio of incorrectly estimated states to the total number of environment states. One dataset evaluation consists of two comparisons, each corresponding to the given environment representation. Table 5.1 shows the evaluation resulting from the 'Aruba' dataset as described in Section 4.2.1, in which the people presence is given qualitatively (binary signal) or by means of 3D occupancy grids.

Table 5.1: *Aruba dataset results: Model errors for different exploration strategies and spatio-temporal models [%]*

	Spatio-Temporal model							
	People Presence				*3D Grids*			
Strategy	*SM*	*LM*	*FT*	*GM*	*SM*	*LM*	*FT*	*GM*
Round Robin	09.3	09.7	06.5	07.5	08.9	09.3	05.6	05.8
Random	08.9	09.5	09.2	07.5	08.7	09.0	08.3	07.2
Greedy	08.5	08.7	07.0	09.4	07.7	10.9	06.2	07.1
Monte-Carlo	08.5	08.9	05.8	06.4	08.0	08.3	05.0	05.7
Novelty-driven	08.5	08.9	**05.7**	06.1	08.0	08.4	**04.9**	05.4

The results of the 'Aruba' dataset summarized in Table 5.1 show that the combination of FreMEn with the novelty-driven or Monte-Carlo strategies reduces the model error by more than 40% when compared to the worst performers. Nevertheless, the combination of FreMEn and the novelty-driven strategy performs slightly better than the combination of the same model with the Monte-Carlo one. One may think that the greedy strategy would be the best performer since it always chooses the room with higher entropy, but in most situations, this strategy fails to maintain an up-to-date model. For example, in the case of noisy and unpredictable signals in a given room, the robot will attempt to focus its attention mainly on that room. While this is a logical behaviour – not being able to model the location, the robot will gather the data about it through direct observation, it might not be really desirable, because the robot might not be getting valuable data at all. Also, this behaviour would mean that the robot would not observe the remaining rooms, since the entropy of the current room would be higher due to the higher uncertainties.

Figure 5.4 shows that the FreMEn model error is higher during the first days, but that as soon as the environment patterns are identified the error decreases substantially. This demonstrates that this strategy allows for quick identification of the environment patterns and to lower errors in the long-term. Since more than 99% of the cells in the 'Aruba' occupancy grids represent empty space or static objects, the model error (Equation 5.2) is calculated for the cells that change their occupancy at least once.

Table 5.2: *Brayford dataset results: Model errors for different exploration strategies and spatio-temporal models [%]*

	Spatio-Temporal model							
	People Presence				*Visual Features*			
Strategy	*SM*	*LM*	*FT*	*GM*	*SM*	*LM*	*FT*	*GM*
Round Robin	23.7	23.7	16.3	20.2	25.7	27.0	12.7	17.9
Random	23.7	23.8	23.0	23.8	25.9	27.0	25.2	20.3
Greedy	20.2	22.3	19.2	20.1	29.9	29.3	24.4	18.6
Monte-Carlo	23.5	23.5	16.4	19.3	25.6	27.0	12.3	16.9
Novelty-driven	23.4	23.5	**15.2**	19.4	25.6	27.0	**12.1**	17.1

The model errors of the 'Brayford' dataset as shown in Table 5.2 again indicate that the most faithful environment representation is based on frequency-enhanced temporal models (see Section 3.2.3) in combination with the novelty-driven strategy. The improvement is more prominent in the case of visual features models. The reason for this might be that the visibility of image features tends to follow regular patterns given by the daily illumination cycle, whereas the presence of people can be influenced by unexpected events.

Figure 5.4 shows that initially, the GMM model achieves the lowest error, but in the long-term, it is outperformed by FreMEn. This is caused by the fact that the GMM model

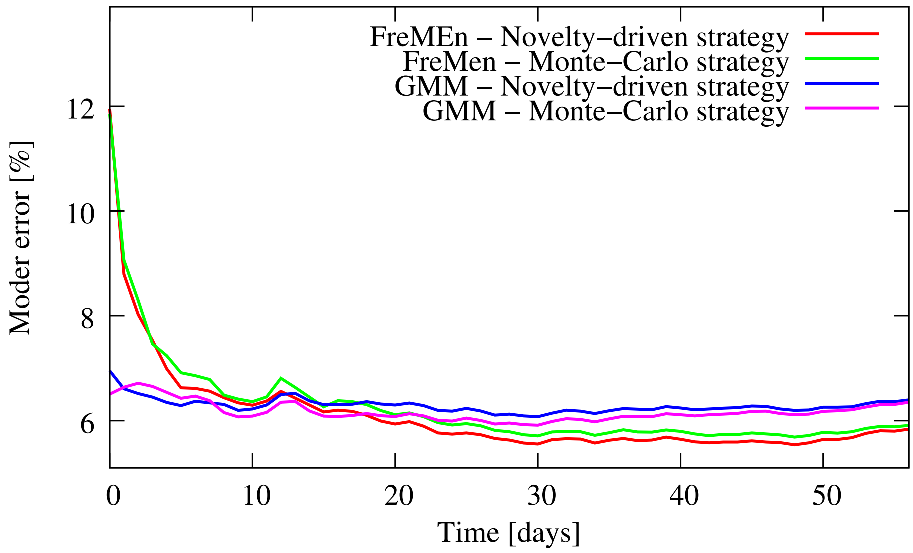


Figure 5.4: *Comparison of the average error of the novelty-driven and Monte Carlo exploration strategies.*

is tailored to represent daily periodicities, while the FreMEn model has to identify the patterns of changes from the data by itself. After several days, FreMEn identifies several important periodicities (not only the daily one) and its prediction capability improves, allowing it to better schedule observations and decrease the model error. Figure 5.4 also shows that the novelty-driven strategy performs slightly, but consistently, better than the Monte-Carlo one. In the experiments performed, the novelty-driven strategy is able to identify one or two unexpected observations per day.

5.5.2 Exploration vs. Exploitation

In the above experiments, the robot's exploration ratio e was set to 0.5. Thus, the robot could spend 50% of its time gathering data about its operational environment. However, such a ratio is unrealistic – the robot has to spend some time replenishing its batteries, and we have to assume that it should perform other tasks as well depending on the application. Moreover, we have to assume that the purpose of the robot is not in creating precise environment models, but to perform useful tasks. Thus, exploration is just an instrument to obtain and maintain knowledge to improve the robot's performance. If the robot spends too much time on exploration, it would not be able to exploit the obtained knowledge in its everyday activities.

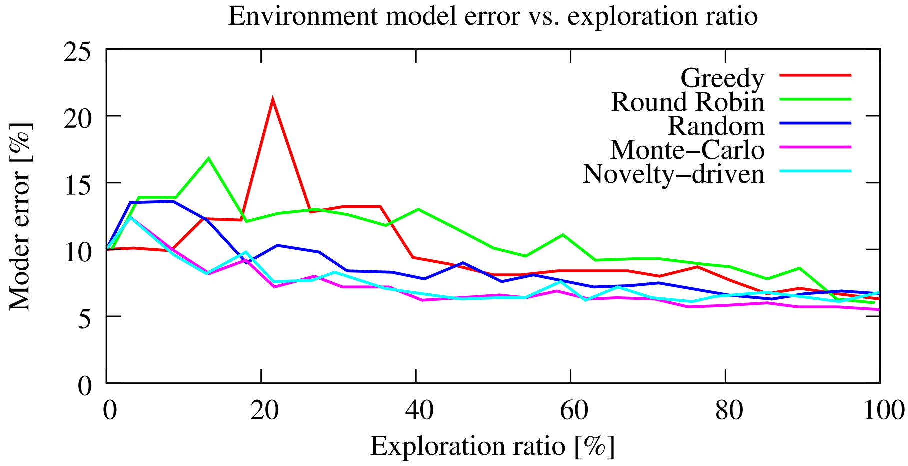


Figure 5.5: *Exploration vs. exploitation analysis: The influence of the fraction of time spend with exploration on the performance of the exploration strategies.*

The efficiency of the individual exploration strategies with different exploration ratios for predicting person presence on the Aruba dataset was evaluated. The Frequency Map Enhancement model has been compared with four different exploration strategies by fixing the exploration ratio to a value between 0 and 1, and let the robot explore the Aruba environment for two consecutive weeks. The obtained result error of the model obtained is shown in Figure 5.5. The results indicate that if the fraction of the time that the robot can spend on actual exploration is low, the dynamic models might make wrong assumptions about the environment changes and perform worse than their static counterparts – this is especially notable with the Greedy and Round Robin strategies. However, this effect can be mitigated by a proper exploration strategy – the graph shows that both Monte Carlo and novelty-based strategies improve the model even if the robot cannot spend too much time on exploration.

Note that the initial model error is 10% – this is caused by the fact that the Aruba dataset represents the presence of people in 10 different areas and the flat has only one inhabitant. Without any observations, the robot simply assumes that the flat is empty, which results in 10% error.

5.6 Case Study: Info-terminal

The concepts behind the lifelong exploration described in this chapter were used to enhance the performance of a service robot in a real-world care home. As seen in the previous

(a) User accessing the "info-terminal". *(b) The interface.*

Figure 5.6: *The mobile "info-terminal" deployment in the STRANDS care scenario.*

sections, the combination of spatio-temporal world representations with scheduling strategies enables a mobile robot to gather more information about its operational environment changes, and thereby improve its performance over time. Based on this concept, a mobile "info-terminal" based on a Scitos G5 platform was developed and deployed in the care scenario described in 3.1.

The purpose of "info-terminal" system is to allow users to access information relevant to them at the most appropriate times and locations. Thus, the exploration strategy described in this thesis provides to the system the means to learn **where** and **when** to provide relevant information to a high number of users. The information displayed by the mobile robot can range from weather forecasts to the daily canteen menu as show in Figure 5.6. A description of the system and long-term study on the impact of such system in the resident's life can be found in (Hanheide et al. 2017). The system has shown to be able to build accurate spatio-temporal model of interactions over time that contributed to an overall increase of interactions between the robot and the residents. Additionally, the same spatio-temporal models were used to efficiently reason which information should be immediately displayed at the different times and locations where the robot decides to perform an info-terminal task.

Figure 5.7 shows the resulting models of the "info-terminal" operation. Note that the different locations exhibit different periodicities. For example, the cafeteria exhibits approximately 3 hour periodicity, which matches the typical human meal routines. Moreover, Figure 5.8 demonstrates that the robot is able to gather more interactions over time, revealing once again that is able to reason about where and when its more useful.

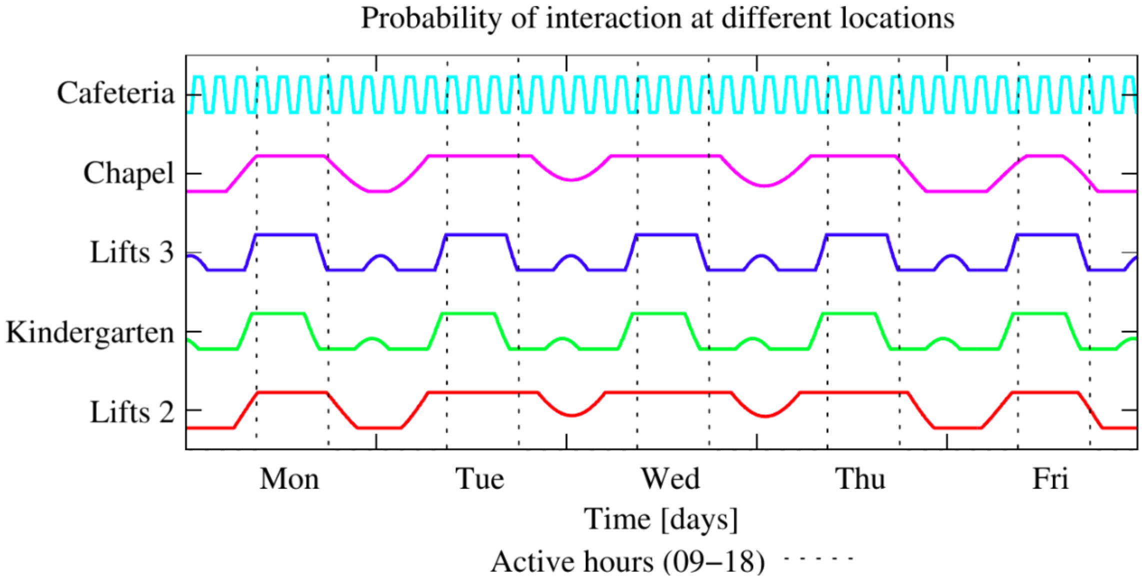


Figure 5.7: *The temporal models learned for a set of locations in the environment (Hanheide et al. 2017).*

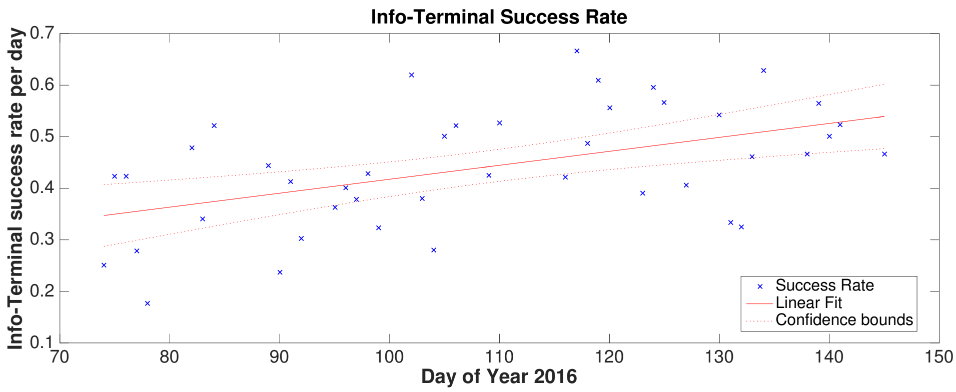


Figure 5.8: *Interaction success rate over time (Hanheide et al. 2017).*

5.7 Summary

In this chapter, the concept of lifelong exploration of changing environments was presented. Assuming the robot's operational environment is subject to perpetual change requires a method that can model and predict these variations. The purpose of lifelong exploration is not only to obtain the environment structure and keep it up-to-date with any changes but also to allow the robot to observe and understand the world changes.

The problem of lifelong exploration can be tackled by combining information-gain-based exploration strategies with probabilistic dynamic environment models. To verify this hypothesis, the performance of five exploration strategies and four temporal models were compared on real-world data gathered over the course of several months. The combination of spectral-based temporal models with information-gain-based novelty-driven strategies resulted in an intelligent exploration behaviour that improves as the environment knowledge becomes more refined.

Analysis of the robot behaviour shows that when introduced to a new environment, the robot prefers to explore unknown locations. After it has obtained the spatial models, it starts to revisit these locations in order to learn about their dynamics. Finally, the learned dynamics allow the robot to schedule which locations to visit at which times and adapt this schedule in the case of unexpected observations.

The evaluations performed in this chapter involved several assumptions to simplify the problem. The first assumption was that the time the robot spends moving to a particular location is negligible compared to the time it takes to make an observation. The second assumption was that the locations of observations were predefined and that the robot could position itself with perfect accuracy. The third assumption is that the observations are error-free, i.e. there is no noise on the sensory data.

The aforementioned simplifications enable to validate the concept of lifelong exploration and to further understand which challenges must be tackled. Thus, the lifelong exploration has shown to be able to maintain the robot's world models over time as well as the ability of the robot to better reason over time, which is essential to ensure the long-term operation of mobile service robots. While these assumptions were needed for validation purposes in this work due to the known difficulties of ground-truthing when comparing exploration strategies, the study conducted further enabled the development of a full 4D metric-based spatio-temporal exploration, as described in Chapter 6.

6

4D Lifelong Exploration

This chapter addresses the problem of acquiring and maintaining a full 4D metric-based spatio-temporal model during the robot's long-term operation. While the previous chapter focused on validating the concept of lifelong exploration and evaluating the performance of several scheduling strategies and world representations at a higher level of abstraction, the exploration approach described in this chapter aims at building a full metric representation of the environment that accurately represents the 3D robot's operational environment over time. Comparatively to the work described in the previous chapter, the mobile robot was used as a completely virtual entity with no physical parameters or constraints that have an impact on the robot's performance. In the method proposed in this chapter a real mobile robot is used that not only has to deal with noisy observations but also has to plan the path to perform the observations and to localise while the locations to observe are not limited to a specific set of locations. Thus, the overall system complexity to enable a metric-based 4D lifelong exploration and mapping strategy is higher. The exploration approach proposed in this chapter is designed not only to integrate sensory data captured at different locations and times into a 3D dense spatio-temporal model but also to plan the path to these locations and to safely navigate to them.

The application of information-theoretic scheduling methods described in Chapter 5 to time-dependent probabilistic environment representations results in a continuously improving exploratory behaviour, which evolves with the knowledge of the environment dynamics. Thus, this allows the mobile robot to create, maintain and refine its 4D environment representation as a part of its daily routine and improve the robot's efficiency in performing other tasks at the same time, which is essential for long-term mobile robot operation in changing environments.

The proposed method extends the concept of lifelong exploration presented in Chapter 5, which builds frequency-enhanced spatio-temporal models from sparse and non-uniform observations and examines the performance of various exploration strategies and dynamic models. However, the method described in Chapter 5 was based on several simplifications that make its real-world use difficult: it assumes that the topology of the environment is known a-priori and it neglects the fact that navigating between different locations requires different time durations. In other words, the robot simply selects which pre-defined topological locations should be visited at particular times in order to create and maintain local dynamic models on top of an a-priori known topological structure.

The work presented in this chapter describes an exploration pipeline that starts without any a-priori knowledge about the robot's 3D operational environment. The locations to be observed are not selected from a predefined set, but the robot infers the locations from the 3D structure itself. Thus, it considers not only the information gain obtained by visiting a given location but also its reachability and the time it takes to navigate there. This results in a life-long exploration system that allows to create and maintain global 4D spatio-temporal representations of real, changing environments without prior knowledge of their topology. To evaluate the method, a comparison with a standard exploration method performed during a 5-day-long simulation and real-world experiments performed in a human-populated environment has been made.

6.1 From Simulation to Real World Deployment

As stated before, robotic exploration methods usually consist of two alternating phases: planning and mapping. Considering that the environment is constantly changing, both planning and mapping have to take into account the notion of time. Thus, 3D mapping has to explicitly model the environment dynamics and becomes “4D mapping”. The planning has to determine not only which locations to explore but also when to perform the exploration. Other activities which form part of the robot’s daily routines may also be scheduled here since a robot in a real-world application would have to balance its exploration activities with other activities that exploit the current spatio-temporal knowledge.

The proposed exploration system is composed of five main modules: the *Spatio-Temporal Model* that maintains the environment map, the *Scheduler* that determines the robot activity, the *Planner* that calculates which locations are to be explored, the *Executioner* that acts as a bridge between these modules, and the Robot’s navigation and sensing systems. The robot’s activity consists of separate exploration tours during which the robot leaves its charging station, navigates to a set of locations, where it uses its depth camera to observe the environment, and finally docks to its charging station using a precise marker-based localization method described in (Krajník et al. 2014). In this section, an overview of the exploration system and then details of its main modules are provided.

6.1.1 Notation

The notation used over the following sections to describe the 4D lifelong exploration strategy is as follows:

- s denotes the set of world states;
- p denotes the probability of a given state;
- $\mathcal{S}$ denotes the set of world states;
- $\mathcal{P}$ denotes the set of prominent spectral coefficients;
- μ denotes the mean probability;
- ω denotes the natural frequency;

- α denotes the components of the spectrum of observations;
- ς denotes the saturation function;
- Ω denotes the set of candidate frequencies;
- I denotes the information-gain;
- E denotes a the score of a given candidate location;
- $\mathcal{G}$ set of goals to observe.

6.1.2 System Overview

The overall system structure and its most important data flows are shown in Figure 6.1. Every 24 hours at midnight, the *Scheduler* sets up an activity plan for the upcoming day, which is partitioned into several time slots of the same duration. To determine which time slots are to be used for exploration and which ones to use for charging, it uses the *Planner* and the *Spatio-Temporal Map* to estimate how much information would be obtained by performing exploration at each of the time slots. In particular, the *Scheduler* sends the start time of a particular time slot to the *Spatio-Temporal Map* and the number of locations to visit to the *Planner*. The *Spatio-Temporal map* then predicts the probability and entropy of the environment states for the given time and passes the model to the *Planner*. The *Planner* then generates a sequence of candidate locations to visit, querying the *Spatio-Temporal Map* for the expected information gain at those positions and the *Reachability Map* for the probability that the robot will be able to navigate to those locations. The *Planner* then selects a number of locations to visit, where the number is given by the *Scheduler*, and reports the overall information gain back to the *Scheduler*. Based on the estimated information gain for each time slot, the *Scheduler* decides which time slots are to be used for exploration and which ones to use for recharging. The schedule-generation process is computationally expensive, mainly because the robot has to calculate the potential information gains across many locations and times. The entire schedule-generation process takes approximately two minutes and is performed during recharging. While the generated schedule ensures that the robot will tend to explore the environment when it is more likely to exhibit changes, the plans (sequences of points)

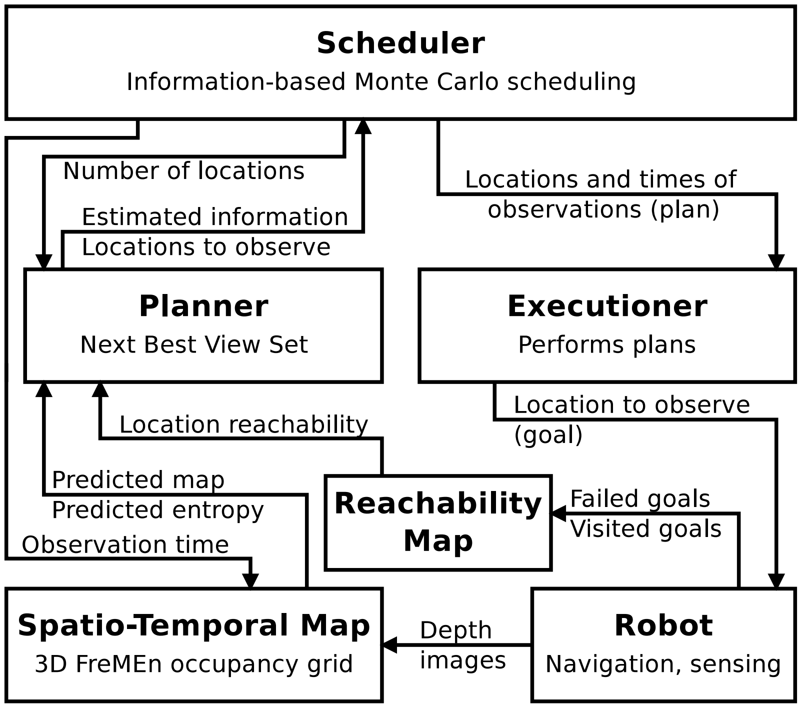


Figure 6.1: *Exploration system modules and main data flows*

generated by the *Planner* during the process of schedule generation might not be suitable at the time of their execution because the environment might change in a way that was not originally predicted.

Thus, at the beginning of each time slot allocated for exploration, the *Scheduler* queries the *Planner* for a new plan. The *Spatio-Temporal Map* predicts a temporary 3D occupancy grid, which is used to estimate the information gain and the *Reachability Map* for the given time. The *Planner* uses this information to decide which locations to visit and the *Executioner* determines their order and passes these goals one-by-one to the *Robot*'s navigation system. The *Robot* monitors whether the required locations (goals) were reached and passes this information to the *Reachability Map*. If a goal is reached successfully, the *Robot* uses its pan-tilt unit and depth camera to update the temporary 3D grid using the method in (Levoy 1990) and marks which cells were observed. After each 3D sweep, the updates made in the temporary 3D grid are propagated to the *Spatio-Temporal Map* using Equation (6.2). The Figure 2.5 illustrates the basic concept of the system – the entropy grid, which indicates the most informative locations to observe. Note, that the entropy maximum is in the centre of the unexplored area – the Planner would prefer this location over the others.

6.1.3 Spatio-Temporal Map

The Spatio-Temporal map used in this system is based on a uniformly-spaced 3D occupancy grid extended by the Frequency Map Enhancement (FreMEn) concept as described in Section 3.2.3. While in Chapter 5 the non-uniform FreMEn model is calculated incrementally using Equations 3.5 and 3.4, in this approach the observations are processed in a batch mode. Moreover, in this exploration system a simplified scheme of transformation between the time domain $s(t)$ and the frequency domain $S(\omega)$ is proposed. Assuming that the spectral representation $P(\omega)$ of the state $s(t)$ consists of a small number of frequencies ω_i, phase shifts $\texttt{arg}(\alpha_i)$ and amplitudes $|\alpha_i|$, the probability $p(t)$ of the state $s(t)$ can be calculated as

$$p(t) = \varsigma(\mu + \sum_{i=1}^{n} |\alpha_i| cos(\omega_i t + \texttt{arg}(\alpha_i))), \tag{6.1}$$

where μ corresponds to the 'static' probability of the state $s(t)$, n is the number of periodicities modelled, and $\varsigma()$ ensures that the result of Equation (6.1) is bounded between 0 and 1. To reflect the fact that we cannot be absolutely certain when predicting a given state, function $\varsigma()$ limits the $p(t)$ between 0.05 and 0.95.

To obtain the parameter α_i from m measurements of the state s taken at times t_k, we first calculate the value of μ as an arithmetic mean of all past observations $s(t_0)$ to $s(t_{k-1})$. Then a set of candidate frequencies Ω is created, which represent the periodicities of the hidden processes that affect the state $s(t)$. Finally, we establish the amplitudes α_c as

$$\alpha_c = \sum_{k=1}^{m} (s(t_k) - \mu) e^{-j2\pi t_k \omega_c}, \tag{6.2}$$

where ω_c are elements of the set Ω. Note that the parameter β_k calculated in Equation 3.4 is not used in this scheme, reducing the memory requirements of the model, but resulting in slightly less accurate model.

Then, we order the frequencies ω_c according to their amplitude α_c, select the first n of them and store these as parameters ω_i,φ_i and α_i, which are used in Equation (6.1). Note that unlike the traditional DFT described in Section 3.2.2, Equation (6.2) allows to update the spectral model as new observations of the state $s(t_k)$ are obtained. While faster to calculate and allowing for non-uniform sampling, the proposed representation does not ensure precise reconstruction of the original sequence $s(t)$ but typically results in $\sim 2\%$ reconstruction error.

The *Spatio-Temporal Map* applies the FreMEn concept to occupancies of cells in a 3D occupancy grid. Thus, each cell contains its own set $P(\omega)$ that allows to calculate the probability of the cell's occupancy for any given time. This model is updated by Equation (6.2) every time the cell is observed and its state $s(t_k)$ is measured.

Both Equations (6.1) and (6.2) are derived from the continuous formulation of the Fourier transform by Rahman (2011), but unlike the classic discrete Fourier transform (DFT), Equations (6.1) and (6.2) simply do not assume time-uniform sampling of the state $s(t)$. In the case of uniform sampling with period Δt, i.e. $t_k = k\Delta t$, Equation (6.2) would become equivalent to the standard DFT.

Temporal model design

The set Ω of candidate frequencies in Equation (6.2) defines which periodicities will potentially be captured by our model. The elements of Ω can be chosen arbitrarily, but one should consider that larger Ω enables a finer representation of time at the expense of higher memory consumption of the spatio-temporal model. In the experiments conducted, the set Ω consist of 24 elements ω_i, which are distributed in the same way as in the traditional FFT, i.e. $\omega_i = (24 \times 3600)/i$. This allows to model several periodicities ranging from one day to one hour. To model spatio-temporal dynamics of office-like environments, one could extend the set Ω by adding day-to-week periodicities as in Chapter 5. However, the duration of the real-world experiments performed were no longer than five business days.

The parameter n in Equation (6.1) determines how many periodicities of Ω are actually considered in the state prediction. Previous work indicates that a good choice of n is 2, which typically results in modelling week- and day-long periodicities in indoor environments and year- and day-long cycles outdoors. Note that setting n to 0 means that the probability $p(t)$ becomes a constant as in traditional spatial-only representations. Similarly, non-periodic dynamics will cause the coefficients α_i calculated by Equation (6.2) to be close to 0, which will cause the $p(t)$ to be almost constant as well.

6.1.4 Predicting the information gain

Similarly to the work described in Chapter 5, the FreMEn model can predict the probability of each cell being occupied, and it also allows to estimate the amount of information that the robot obtains by observing a particular cell at a given time. The amount of information $I(t)$ obtained by observing a single cell at time t can be calculated as the difference between the cell's *a-priori* entropy $E(t)$ and *a-posteriori* E_r entropy, i.e. $I(t) = E(t) - E_r$, which are functions of the cell's occupancy probability before and after the observation. Since the cell's occupancy probability is considered a function of time and we assume that the robot observes a given cell long enough to determine its state with certainty $p_c = 0.95$ (i.e. the probability of the cell being occupied after the observations becomes either 0.05 or 0.95), the expected information gain at time t is

$$\begin{aligned} I(t) &= -p(t)log_2 p(t) - (1-p(t))log_2(1-p(t)) \\ &\quad +p_c \log_2 p_c + (1-p_c)\log_2(1-p_c), \end{aligned} \tag{6.3}$$

where $p(t)$ is the probability of occupancy of a given cell at time t calculated by Equation (6.2). Using the predicted occupancies and entropies, the *Spatio-Temporal map* allows to estimate the amount of information that the robot will obtain by observing a particular part of the environment at a particular time using its depth camera. Since the robot uses its pan-tilt unit to create a 360° 'sweep' of its surroundings, the *Spatio-Temporal Map* implements a function that can estimate the obtained information given the robot's position and the time of observation.

6.1.5 Reachability map

Although the ability of the robot to reach individual locations of the environment can be inferred by the *Planner* from the environment's spatio-temporal representation, some locations might not be reachable due to factors that are not included in the spatio-temporal model, such as transparent obstacles or objects with dimensions smaller than the spatio-temporal grid resolution. To reflect that, the exploration system maintains a *Reachability Map*, which is a 2D (50×50 cm) grid with cells that contain the robot's success rate over the last five attempts to reach that particular location. This information is taken into account when the exploration plans are calculated.

6.1.6 Locations to observe

In this work, it is assumed that moving to and observing one location takes approximately two minutes. Taking into account the time needed to dock to and leave the charging station, the robot can visit 6 locations in a 15-minute time slot.

To determine which locations are to be visited during a given time slot, the *Planner* first generates a uniform 2-D grid of candidate positions $x_i, y_i \in \mathcal{D}$ that cover the operational environment. Then, it sends these positions to the *Reachability Map*, which returns the probability with which the robot will be able to reach these positions, i.e. the *Planner* will obtain a reachability probability $p_r(x_i, y_i)$ for each candidate location (x_i, y_i). If a position (x_i, y_i) is reachable, i.e. $p_r(x_i, y_i) > 0$, the *Planner* forwards the position (x_i, y_i) to the *Spatio-Temporal Map*, which uses the predicted 3D grid to estimate which cells are likely to be observable by the robot's depth camera from the position (x_i, y_i). The *Spatio-Temporal Map* sums the information gain of these cells using Equation (6.3) and reports it to the *Planner* as $I_c(x_i, y_i)$. This allows the *Planner* to create an evaluation $E(x_i, y_i)$ of each candidate location as

$$E(x_i, y_i) = p_r(x_i, y_i) I(x_i, y_i). \tag{6.4}$$

Once Equation (6.4) has been calculated for every (x_i, y_i), the *Planner* starts to generate the locations to visit. First, the *Planner* finds the global maximum $E_{max}(x_j, y_j)$ of $E(x_i, y_i)$, adds (x_j, y_j) and E_{max} to the set of goals $\mathcal{G}$ and sets $E(x_j, y_j)$ to 0. To take into account the fact that the cells observable from (x_j, y_j) are also visible from neighbouring locations but observations at locations close to (x_j, y_j) would not provide the same expected information, the values of $E(x_i, y_i)$ in the vicinity of (x_j, y_j) are decreased proportionally to their proximity to (x_j, y_j) by taking into consideration the sensor range. The aforementioned two steps, i.e. maxima search and suppression of the information gain estimates at the neighbouring locations, are repeated until the number of goals in the set $\mathcal{G}$ equals the number of locations requested by the *Scheduler*. Then, the *Planner* calculates the sum E_G of information gains $E_{max}(x_j, y_j)$ in $\mathcal{G}$ and reports the value of E_G to the *Scheduler* along with the locations in $\mathcal{G}$.

6.1.7 Generating the schedule

Once the *Scheduler* obtains the summarised information gain E_G for every time slot using the aforementioned procedure, it uses a Monte-Carlo-based method to determine which time slots to use for exploration and which ones to use for charging. Thus, the probability that a given time slot will be selected for exploration is proportional to its expected information gain E_G. The generated schedule is then saved and the *Scheduler* is deactivated until the start of the next time slot.

At the beginning of each time slot, the *Scheduler* checks whether the time slot was allocated for exploration and eventually queries the *Planner* for an up-to-date plan for the given time. Then, it forwards the set of locations to observe to the *Executioner*.

6.1.8 Plan execution

The *Executioner* module is responsible for carrying out the plan provided by the *Scheduler*. At first, the *Executioner* uses a 2-opt method (Croes 1958) to establish a sequence in which the planned locations should be visited. Then, it ensures that the robot leaves its charging station, follows the given path while taking measurement at the given locations and returns back to recharge. If the *Executioner* fails to reach a given location, which is typically caused by the location being blocked, it first waits for the location to be cleared. If the location remains unreachable, the *Executioner* simply proceeds with the following location in the plan. After each run, the *Executioner* reports the successes or failures in reaching the planned locations to the *Planner*, which updates the *Reachability map*. This causes the robot to avoid areas that are more likely to be blocked. However, the amount of obtainable information for the neighbouring cells is likely to be high, causing the robot to perform observations in nearby locations in the next exploration run.

6.2 Experimental Evaluation

In order to evaluate the above system, real-world experiments were performed in office environment over five business days. The experimental conditions and the robotic platform used are described in the following sections.

6.2.1 The robot

The platform used in this paper is a Scitos-G5 mobile robot equipped with RGB-D cameras and a laser rangefinder as shown in Figure 6.2. The robot's navigation system is based on open-source software developed during the STRANDS project (Hawes et al. 2016), which extends the navigation stack of Robot Operating System (ROS). The sensor that was used for 4-D mapping was the Asus Xtion RGB-D camera, which was mounted on a pan-tilt unit placed on top of the robot's head. Using this pan-tilt unit, the robot created $360° \times 90°$ 3D sweeps with a 4 m radius at locations it was supposed to observe.

Figure 6.2: *The Scitos-G5 platform used in the experiments.*

6.2.2 Experiment description

To evaluate the proposed lifelong exploration algorithm, a comparison against a method that considers a static environment model is performed. This Spatio-Only (SO) exploration method is equivalent to state-of-the-art, information-based exploration methods, such as (Amigoni & Caglioti 2010).

To compare these two methods, the previously described robot platform running the system described in Section 6.1 was deployed in both a simulated and a real-world office for five business days.

Every midnight, the *Scheduler* generated a schedule for the following day. This schedule was composed of 15-minute-long time slots, of which 48 were exclusively allocated for the SO and 48 for the Spatio-Temporal (ST) exploration algorithm. Since each method had to use half of its allocated time slots to replenish the robot's batteries, the robot performed 24 exploration tours guided by the spatio-temporal method and 24 tours guided by the spatial-only method per day.

Both methods operated as described in Section 6.1. The only difference between them was that the ST method used the predicted (by the *Spatio-Temporal Model*) map while the SO method used the last obtained map. We hypothesize that the use of a predicted map should allow the *Scheduler* to determine when it is more likely to obtain more information and schedule more exploration tours at the times when the office is more likely to be occupied. Moreover, the *Planner* should be able to predict which areas of the environment are likely to change at a particular time and take this into account when generating the locations to explore.

6.2.3 Real-world experiment

The real-word experiment was performed in an open-plan office of the Lincoln Centre for Autonomous Systems (L-CAS), as described in Section 4.2.3. The office consists of a kitchenette, a lounge area and 20 working places that are occupied by students and postdoctoral researchers. During the experiment, two ceiling cameras were used to capture a time-lapse video of the office dynamics, which allowed not only for a location-based ground truth comparison, but also to build a database of the office dynamics.

After five days of exploration, we calculated the amount of changed cells that were observed by the two aforementioned strategies during the individual exploration tours. The Figure 6.3 shows that at the start of the exploration process, the number of cells that changed their state was high, but gradually decreased as the environment structure became known. After the first day, the amount of changes observed by both methods tended stabilize around a value given by noise and the environment dynamics. During the second day, the ST method would start to identify the daily routines and the *Planner* would guide the robot to locations that are more likely to exhibit changes – see Figures 6.5 and 6.6 for the spatio-temporal map obtained after the first two days of the experiment. After the

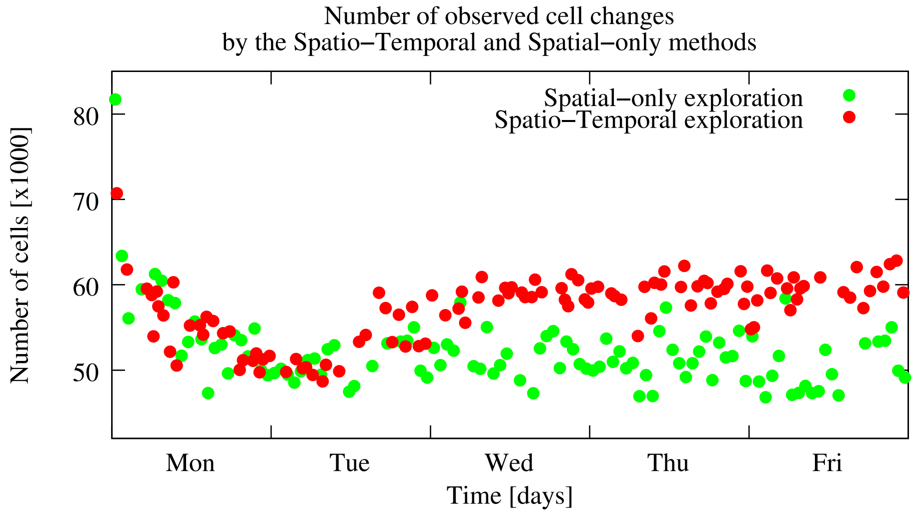


Figure 6.3: *The number of observed occupancy changes by the Spatio-Temporal versus the Spatial-Only exploration methods.*

second day, the ST method would allocate more exploration tours to the afternoon, when the office is more likely to be populated. In fact, there were 30% more tours scheduled for the afternoon than for the morning.

In the last three days of the experiment, the ST method observed more changes than the Spatial-Only one due to its ability to identify the locations and times of environmental changes. In other words, the ST exploration method could plan better **where** and **when** to explore. Figure 6.4 shows a top view of the 4D model obtained after the experiments, in which it is possible to visualise that the areas more prone to change are located near the workstations or social areas that can be found in the office environment.

To establish the accuracy of the models created, six working locations in the office were selected, as shown in Figure 6.6, and the presence of people at these locations over time was manually established. Then, both environment models built by the two exploration strategies were used in order to predict the overall occupancy of these areas (see to Figure 6.6) for every hour of the five-day experiment. Then, occupancies to the ground truth provided by hand-annotated people presence were compared. This allowed to calculate the error of each model in the same way as in Chapter 5, i.e. as an average deviation from the ground truth during the experiment.

Table 6.1 indicates that part of the dynamics of these locations can be explained by periodic processes related to human activity. The researchers working at these six places

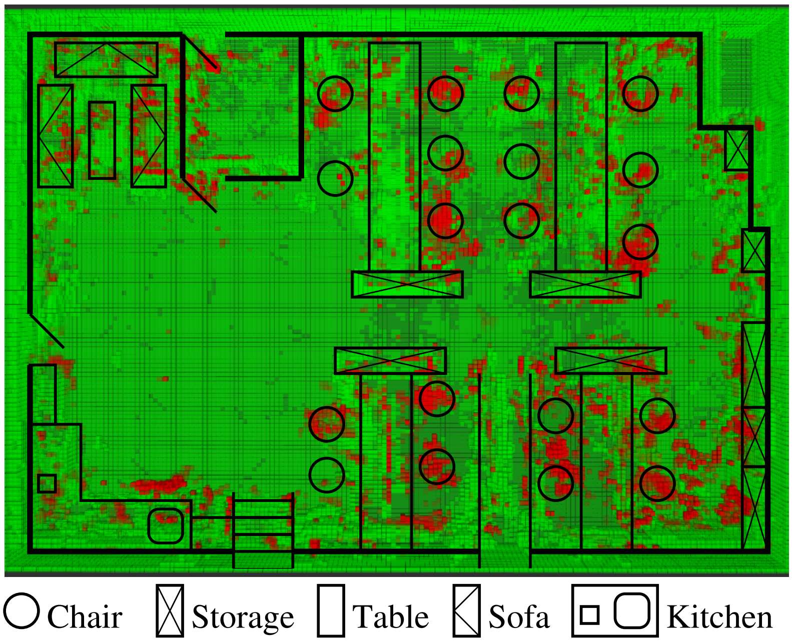
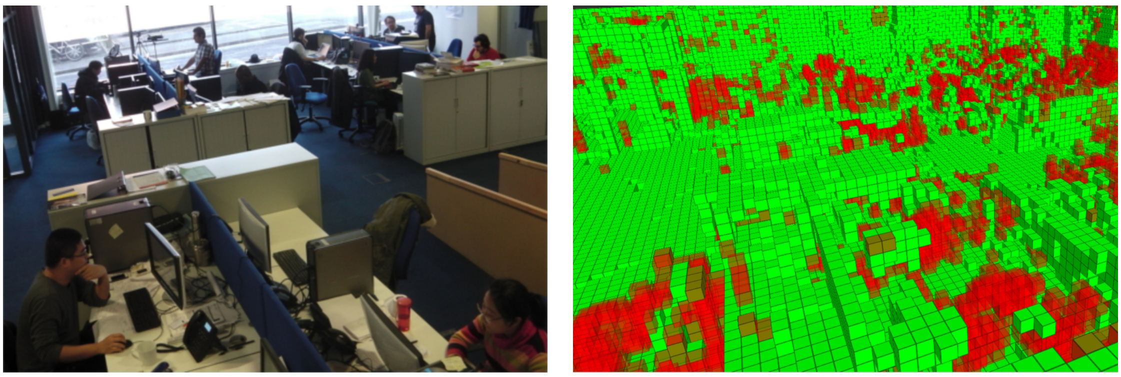


Figure 6.4: Top view of the 4D spatio-temporal model obtained through the lifelong exploration strategy. The static cells are in green and cells that exhibit daily periodicity are in red.



(a) L-CAS office view. *(b) L-CAS spatio-temporal model.*

Figure 6.5: Spatio-temporal occupancy grid of the Lincoln Centre for Autonomous Systems (L-CAS) office. The static cells are in green and cells that exhibit daily periodicity are in red.

had diverse working habits, which caused the error rates to vary across the individual locations. Performing a paired t-test indicates that the error of the 'Spatio-Temporal' environment model is significantly lower than the error of the 'Spatial-Only' method, with a level of confidence of 95%.

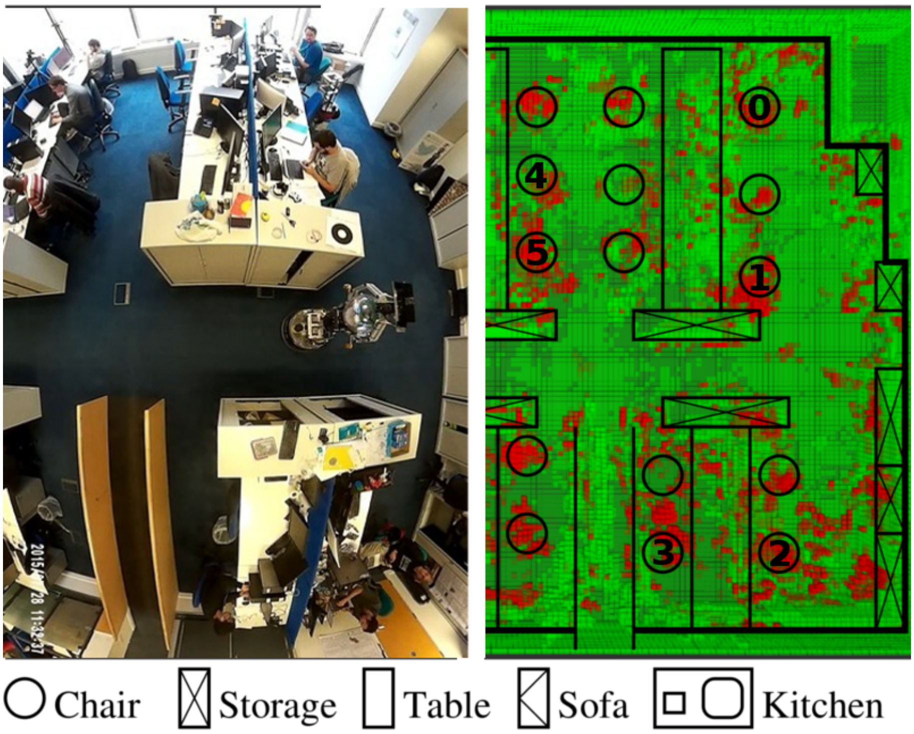


Figure 6.6: The layout, the spatio-temporal occupancy grid and top camera view of the Witham Wharf office. The static cells are in green and the cells that exhibit daily periodicity are in red. The locations for ground-truth evaluation are marked with numbers.

Model type	Location						Avg	StD
	0	1	2	3	4	5	—	–
SO	28	23	43	23	21	29	28	8
ST	20	23	25	19	17	14	20	4

Table 6.1: Overall error of the environment model [%]

6.2.4 Simulated experiment

To speed up testing and to allow for a more representative ground-truth comparison, the 3D MORSE-based simulation was used, as described in Section 4.3.

The experiment was performed in the same way as in the real environment. The number of changed cells captured by both the ST and SO algorithms followed a similar pattern as in the real-world experiment. The outcome of the experiment can also be visualised in the video of Santos (2016).

The ground truth for a single time slot was obtained by configuring the simulation for a particular time and letting the robot perform its 3D sweeps at several locations in order to obtain a complete overview of the environment. This was repeated for every time slot of the experiment, obtaining 480 static 3D grids that represent the environment's evolution over time. The error of a particular model at a given time is calculated as the number of

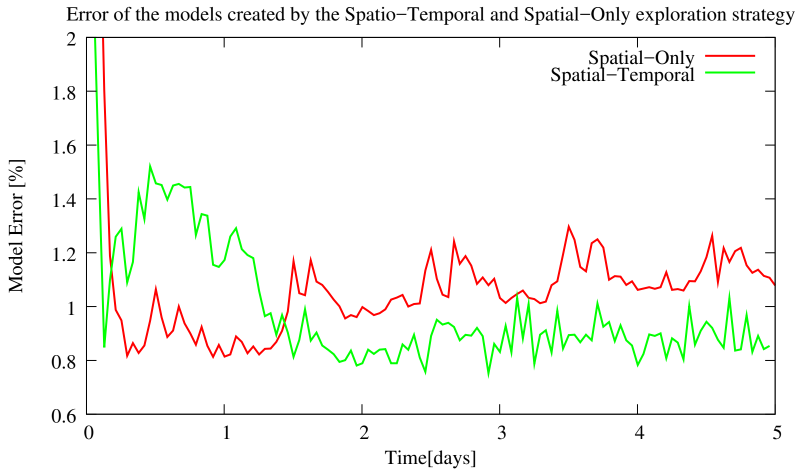


Figure 6.7: *The ratio of incorrectly estimated cells for the Spatial-Only and Spatio-Temporal strategies.*

cells whose states differ from the ground truth divided by the total number of observed cells.

To compare the performance of the SO and ST models, we calculated their errors for each time slot. The error of the ST and SO models over time are illustrated in Figure 6.7. During the second day, the ST model started learning the periodic patterns, which improved its performance.

The experimental results indicate that the Spatio-Temporal method can identify periodic patterns in the environment and take them into account when creating the schedule, which results in more changes observed. The observed changes improve the predictive ability of the Spatio-Temporal model, which allows to construct a better exploration schedule. Note that this is due to the fact that part of the environment dynamics is periodic. If the environment was changing non-periodically, both Spatial-Only and Spatio-Temporal methods would capture a similar amount of changes.

6.3 Summary

In this chapter a 4D lifelong exploration method for changing environments that extends information-driven exploration in order to take into account time is presented. This exploration method is built upon the lifelong exploration concepts described in Chapter 5, which were extended in order to build, update and maintain a 4D representation of a real-world environment. Thus, the 4D representation obtained explicit models of the changing world and can predict these environment states at future times, based on past experience. The predictive ability enables the mobile robot to reason about the most informative locations to explore in the 3D space for a given time.

The experimental results conducted have shown that taking into account the environment changes and integrating them into the robot's world model increases the amount of information gathered compared to approaches that represent the environment as a static structure, ignoring the world changes. Thus, the described method allows for creation and maintenance of spatio-temporal representations that decrease the robot's uncertainty and, consequently, increases the robot's efficiency in long-term scenarios. Additionally, the environment changes detected on a metric level carry relevant information to other modules in the system. To sum up, these experiments allowed to understand not only what is the best strategy for 4D metric exploration but also how quickly the spatio-temporal representation used takes to converge and "identify" the periodic changes in the environment. The method has shown to be able to deal with sparse observations in a fully metric representation.

7 Discussion and Conclusion

In this thesis, the concept of lifelong exploration for mobile robots in changing environments was presented.

While spatio-temporal representations that can cope with the environment changes seem sufficient to enable mobile service robots act intelligently and robustly navigate and localise in these environments, these approaches are specifically aimed at tackling the problem of how to model the environment changes, ignoring the problem of how to efficiently learn these models taking into account the robot's time constraints. Thus, this thesis addressed the problem of building and updating these models given the robot's time constraints resulting from its duties.

An extensive survey of the literature on mobile robotic exploration and world representations taking into account the problem of modelling changing environments was also presented. This review allowed to understand not only what mobile robotic exploration consists of and how environment changes can be modelled but also which direction to take in order to tackle the problem of maintaining and building world models with mobile robots that have to perform other tasks, and consequently can only perform mapping at certain times of the day. The review of the state-of-the-art on mobile robotic exploration allowed to understand how a mobile robot can autonomously decide where to observe next in order to build its world model and the concepts on which these strategies are built upon. Nevertheless, these previous exploration strategies were developed and designed assuming that the world does not change and thus the exploration task ends with the completeness of the world model. An overview of spatio-temporal representations was also presented, which was necessary to understand how to model changing environments, what are the requirements and which type of environment changes are aimed for. While these representations are able to model the environment changes, the mobile robot did not take an active part in the mapping process, i.e., it did not choose where or when new observations have to be performed.

Before proceeding to the main contributions of this thesis, a method to benchmark and validate lifelong decision strategies for keeping the robot's world models up to date was proposed. The typical benchmarking strategies in previous works are suited for mapping and localisation methods that do not take into account the changing nature of the environment or the robot's ability to take decisions about where and when to go in the long-term. Thus, to validate the methods proposed in the scope of this thesis that are essential to ensure reliable and robust performance of the robot during long-term operation, simulation environments that rely on ambient sensors to replicate real-world scenes were proposed.

Then, the main foundations that enabled the development of the lifelong exploration strategy were presented. Firstly, the spatio-temporal representation used in the development of the lifelong exploration strategy was described, i.e., the FreMEn model. The FreMEn spatio-temporal model is built upon the concept of Fast Fourier Transform (FFT) and enables the identification of periodicities in the environment changes (Krajník et al. 2014a). Thus, when applied in this thesis to a commonly used 3D occupancy grid, this model allows to have occupancy probability functions of time for every cell in the grid. Secondly, a study on the ability to model all the observed environment changes while ensuring the model is compact enough so it can be used in real world situations was conducted. This study has showed that the model is able to achieve significantly low errors while keeping the memory requirements low. The model predictive capability that results from the exploitation of the periodicities in the environment changes was linked to information-theoretical concepts showing that modelling the environment states as functions of time enable the extension of information-based exploration strategies in order to also reason over time.

Following the above line of reasoning, the concept of lifelong exploration was finally presented and described in detail. While the main goal of the exploration strategy is to build and maintain a metric based model of the environment, due to the novelty and complexity of the problem, the concept was first studied and validated assuming that the topology of the environment is known *a priori* and by using long-term semantic datasets. The results have shown that a lifelong exploration strategy based on a Monte Carlo method in combination with the FreMEn model was able to build a significantly more accurate model of the environment compared to other strategies and models. In fact, the experiments demonstrated that the robot is not only able to build the model, but also to use the model in order to reason about the best times and locations to observe, i.e., resulting in a self-improving exploratory behaviour.

Finally, a 4D lifelong exploration method built upon the above studied concepts was presented. While in the previous study several simplifications were made to fully understand the concept of lifelong exploration and which environment models and scheduling strategies suit the best the needs of a mobile service robot, in this method the approach was taken to the metric domain, increasing the complexity of the problem. For example, compared to the previous study, the environment topology is not known *a priori*, the set of locations to observe are not predefined, the robot has to plan a path and take into account the times of travel. The different modules required to achieve a 4D exploration system were described and a comparison with a classical exploration approach was performed. This comparison was conducted through five business days long real-world and simulation experiments. The purpose of this experiment was to evaluate how quickly a 3D FreMEn-based representation converges and to evaluate if the same reasoning performed over semantic data is possible in the metric domain. This hypotheses was successfully validated and it was shown that after one and a half days, the mobile robot starts improving its behaviour and scheduling the exploration tasks according to the learned patterns of environment changes. The method was also able to maintain a more accurate representation of the world when compared to classical exploration strategies.

As shown by the research aimed at long-term autonomy for mobile robots, representations that explicitly model the time domain allow mobile robots to interpret the environment changes, which improves their efficiency in long-term operation. While a robot that only exploits the knowledge of spatio-temporal changes previously observed is more likely to succeed in its tasks, it will inevitably obtain biased data because it is more likely to operate at times and locations where the certainty of its success is higher. Feeding these biased data results in over-confident models, which lead the mobile robot to ignore certain locations and times, resulting in even more biased observations. This confirmation bias prevents the robot to adapt to new patterns of the environment changes (Kulich et al. 2016) hampering its efficient long-term operation.

To compensate for this confirmation bias, the robot should be allowed to observe situations where the certainty of the given task outcome is low. To address this problem, the concept of entropy has been applied to spatio-temporal representations and used to drive the mobile robot's attention to the locations and times that are more likely to provide unbiased observations with higher information values. This resulted in a system that allows a robot to create and maintain spatio-temporal world models during its routine operation, i.e. without allocating unnecessary time for the model maintenance.

7.1 Future Work

The concept of lifelong exploration described and validated in this thesis opens several questions for further investigation. Beyond the scope of this work, some aspects can eventually be explored in future research in the long-term autonomy field. In particular, how much time the robot should spend on exploration (represented by the 'exploration ratio' e in the experiments presented in this thesis) during the initial stages of deployment, when the environment model is created, and what is the optimal e later on, when the model is just maintained or when the model needs to be re-built due to changes in the environment dynamics. This will function according to the environment dynamics and will be different for different environments and situations. Thus the need to develop a methodology to adaptively determine this ratio depending on the circumstances, which may change over time. In addition, the lifelong exploration could be extended in order to achieve an autonomous system that learns how to automatically adjust its parameters based on the spatio-temporal context.

One can also think of a method that enables the mobile robot to take several observations of the same location from different points of view in order to refine the 4D model and to more accurately model the environment states. This method in combination with the novelty-driven method described in Chapter 5 would result in a more refined and accurate 4D model. Moreover, the experiments described in this thesis were conducted indoor and assumed both a planar environment and an accurate self-localisation system simplifying the mapping and navigation tasks. Thus, extending the approach described in this thesis to outdoor environments and full 6 degrees-of-freedom would allow to extend the method to other applications besides service robots. Additionally, the proposed lifelong exploration strategy could be extended in order to deal with the loop closure problem. To this end, the robot would have to reason which locations and when are they more prone to undergo an appearance change. This would allow to actively learn when different appearances corresponds to same location. Additionally, the above reasoning could be performed taking into account the entire path instead of computing a set of locations a priori.

While the concept of lifelong exploration has been shown to work well in domestic and office environments, in industrials scenarios the requirements and constraints are different, yet it is still necessary to keep the environment model up to date. For example, in a warehouse, the patterns in the environment might change considerably more quickly than in a domestic scenario, so the model predictions tend to be less effective. Additionally, a mobile robot can not just roam around in order to observe the environment where humans and robots have to work in a synchronized way (Heyer 2010). Thus, the need to observe the environment should consider the robot's tasks and where and when they have to be performed in order to perform exploration as well.

One could use the 4D representation that results from the described lifelong exploration strategy in order to learn about objects (Fäulhammer et al. 2017) and human activities (Coppola et al. 2016). The full 3D metric spatio-temporal representation would allow to predict when and where human activities will happen, and thus allow the robot to decide when, where and from which point of view to observe the human activities decreasing occlusions and gathering as much information about the activity as possible.

Finally, it would be interesting to extend the lifelong exploration concept to the case of multiple robots. Here, the complexity of the scheduling problem will increase significantly since it needs to take into account the time constraints of several robots, their current location and which robots are more suitable to visit certain areas.

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A
Fourier Transform

A.1 Continuous Fourier Transform

This appendix provides an overview of the of the Fourier Transform as well as its most relevant properties. The FT decomposes a signal or a function of time into a sum of sinusoidal functions, which are complex exponential functions defined by both an absolute value and a complex argument. The first value represents the amount of a given frequency in the original signal and the latest represents the phase offset of the same sinusoid in the original signal. Thus, the FT enables the representation of functions of time in the frequency domain.

The Fourier Transform of a function g(t) is defined by:

$$\mathcal{F}\{g(t)\} = \mathcal{G}(f) = \int_{-\infty}^{\infty} g(t)e^{-2\pi ift} \quad dt \tag{A.1}$$

The result is a function of f, or frequency. As a result, $\mathcal{G}(f)$ gives how much power $g(t)$ contains at the frequency f and is often called the spectrum of g. The function g can be recovered from $\mathcal{G}$ via the inverse Fourier Transform, which is given by:

$$\mathcal{F}^{-1}\{\mathcal{G}(f)\}\} = \int_{-\infty}^{\infty} \mathcal{G}(f)e^{2\pi ift} \quad dt \tag{A.2}$$

A.2 Discrete Fourier Transform

The DFT is the equivalent of the continuous Fourier Transform for a finite sequence of equally sampled data or discrete signal. Considering $g(t)$ to be a continuous signal and its N equally spaced samples to be denoted as $g[0], g[1], g[2], \ldots, g[N-1]$. The FT of the original signal, $g(t)$, would be

$$\mathcal{F}\{g(j\omega)\} = \{g(t)\} = \int_{-\infty}^{\infty} g(t)e^{-j\omega t} \quad dt \tag{A.3}$$

Thus, considering each sample of $g[k]$ as an impulse having area $g[k]$ and that the integrand exists only at the sample points:

$$\mathcal{F}(j\omega) = \int_0^{(N-1)T} g(t)e^{-j\omega t} \quad dt \tag{A.4}$$

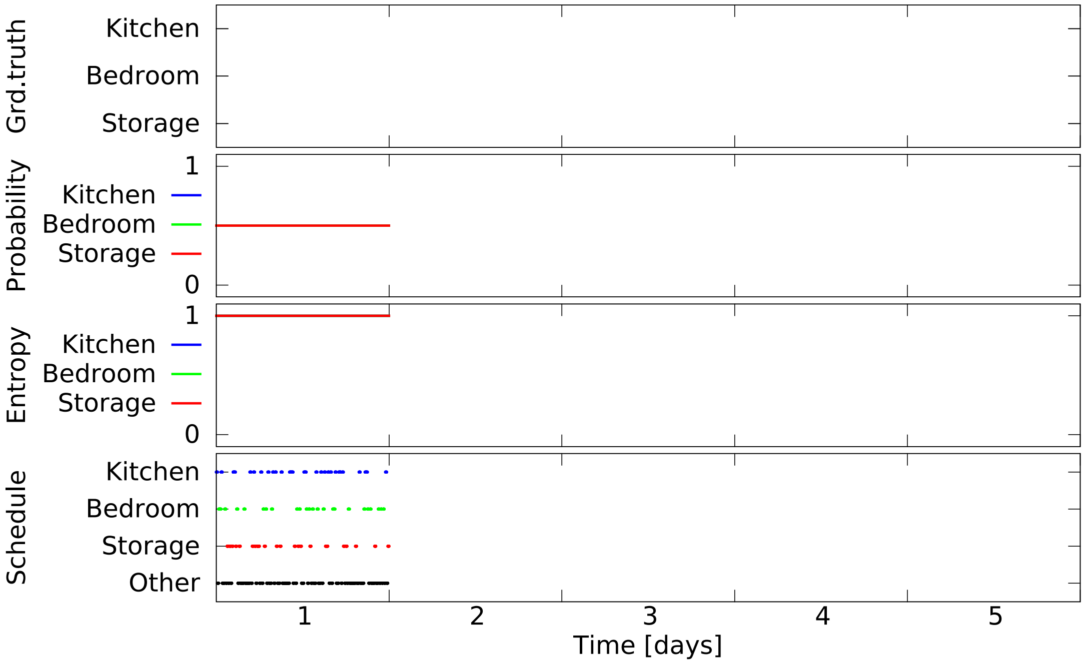
$$\mathcal{F}(j\omega) = g[0]e^{-j0} + g[1]e^{-j\omega T} + \ldots + g(N-1)e^{-j\omega(N-1)T} \tag{A.5}$$

$$\mathcal{F}(j\omega) = \sum_{k=0}^{N-1} g[k]e^{-j\omega kT} \tag{A.6}$$

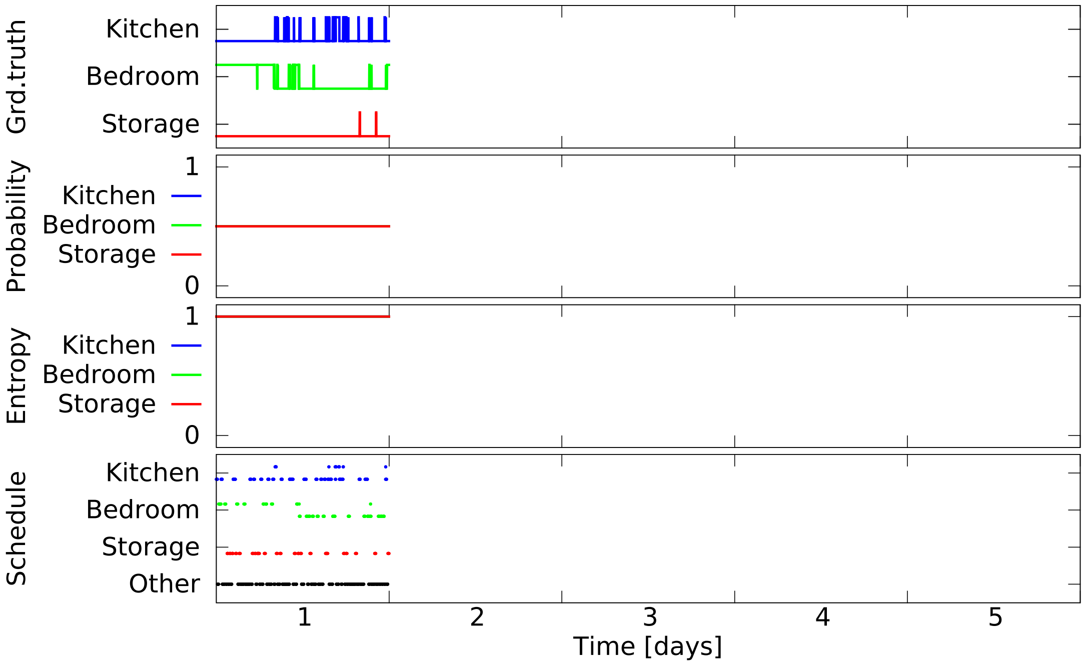
The FFT algorithm allows to efficiently compute the DFT, which allows to calculate the DFT of N in $O(N^2)$ compared to $O(NlogN)$ of the main algorithm. While the original FreMEn model was based on the FFT algorithm, the FreMEn model used in this thesis is an approximation of the original continuous FT.

B
Lifelong Exploration Example

This appendix is an extension of the qualitative exploration example given in Section 5.4, where the evolution of the robot's internal models and schedules are described day-by-day.

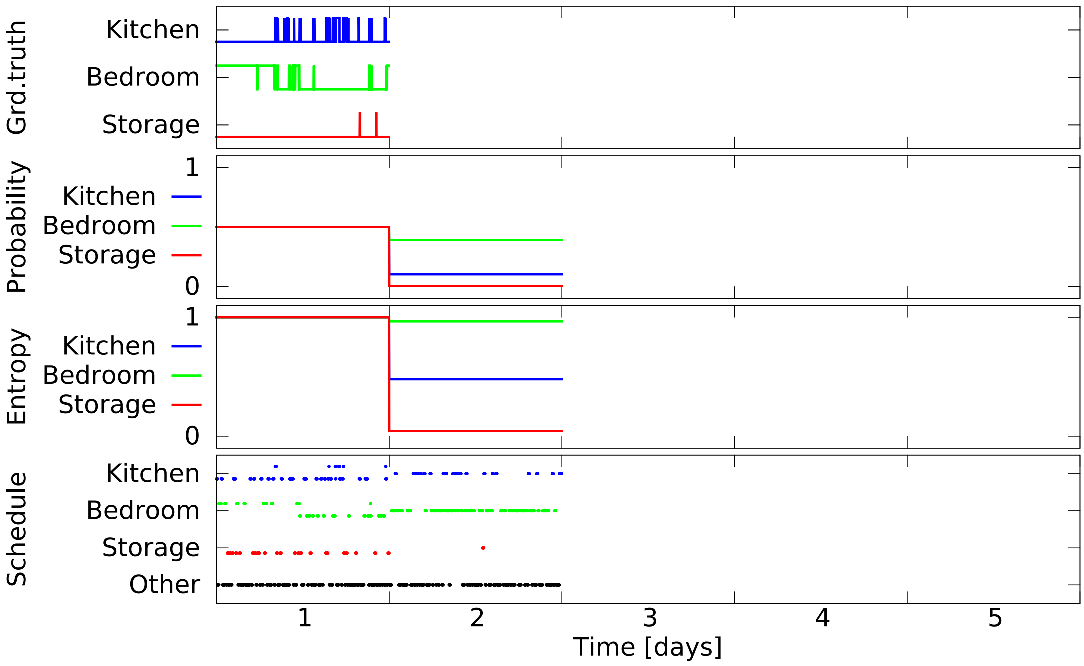


(a) Internal world model and schedule at the start of the day 1.

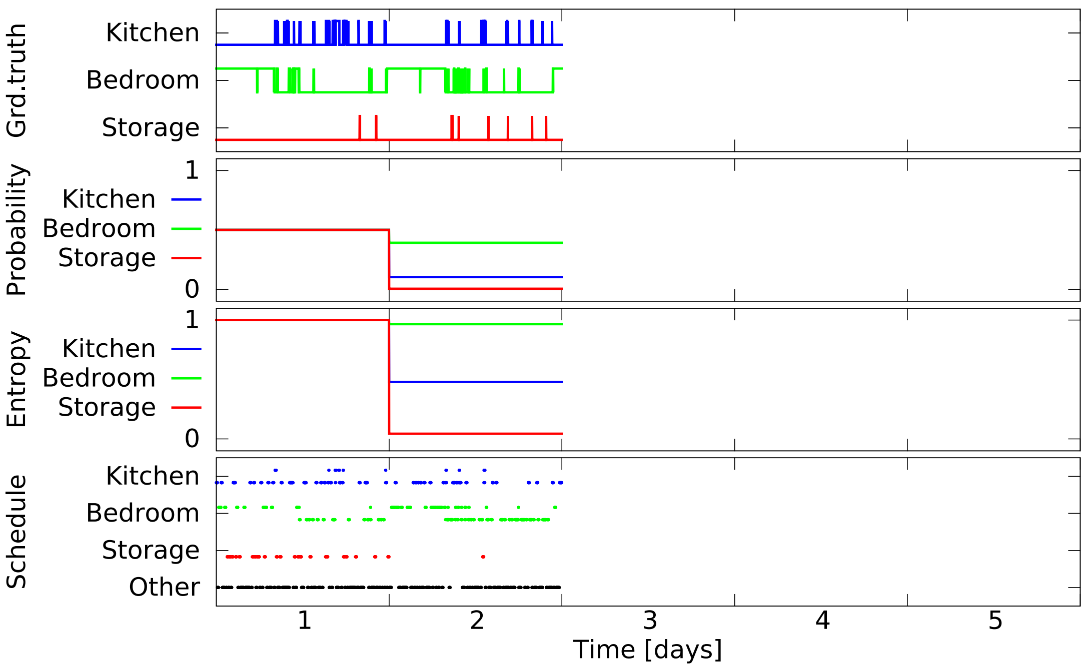


(b) Internal world model and observations made during day 1.

Figure B.1: *Internal world models, schedule and events of day 1 of the Aruba apartment experiment. Initially, robot's world models assume probabilities equal to 0.5, and therefore, there is no location or time preference of observations.*

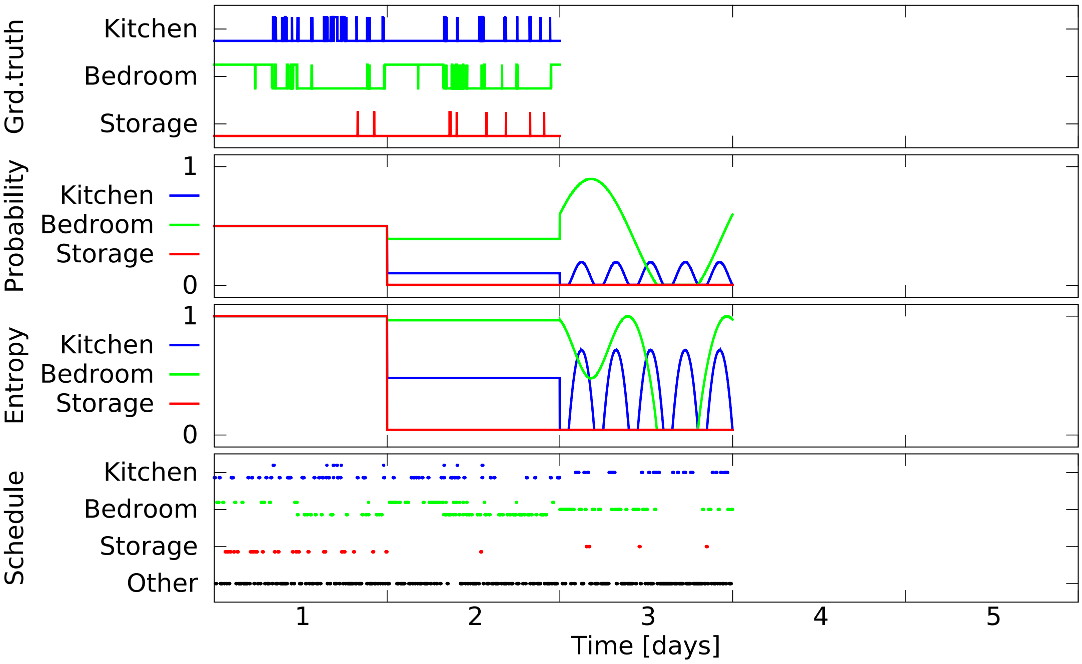


(a) Internal world model (updated based on the observation from day 1) and observation schedule for day 2.

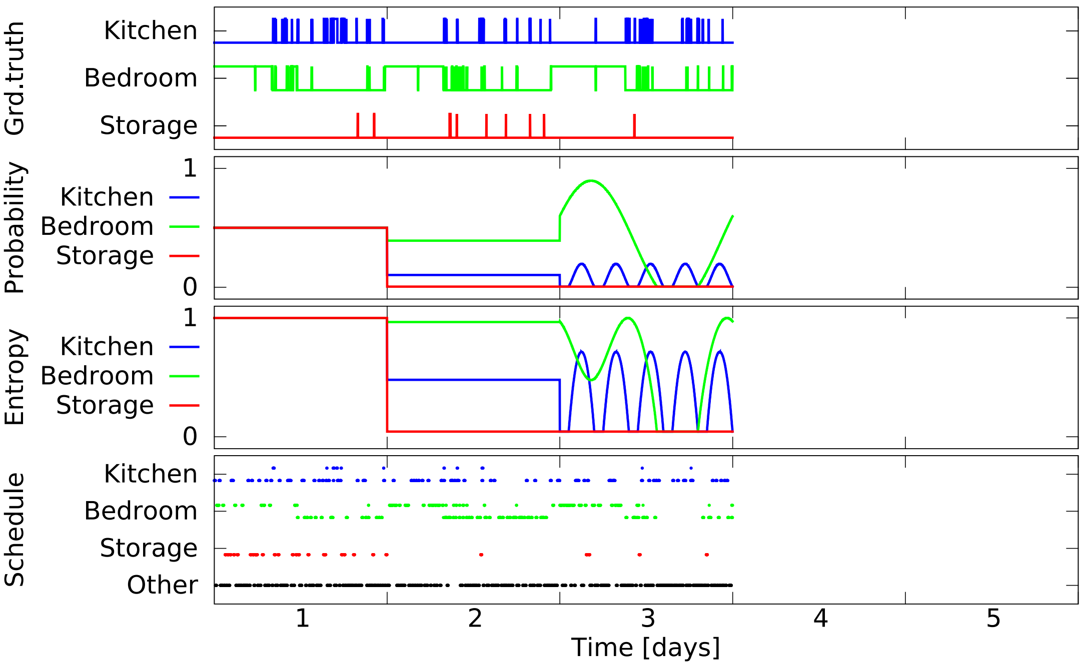


(b) Internal world model based on day 1 observations and observations made during day 1 and day 2.

Figure B.2: *Internal world models, schedule and events of day 1 and day 2 of the Aruba apartment experiment. After the first day, the robot has information about spatial distribution of the human presence, and therefore, it prefers certain locations in its day 2 observation schedule. There is no preference for times, because one day of observations was not sufficient to identify daily patterns of changes.*

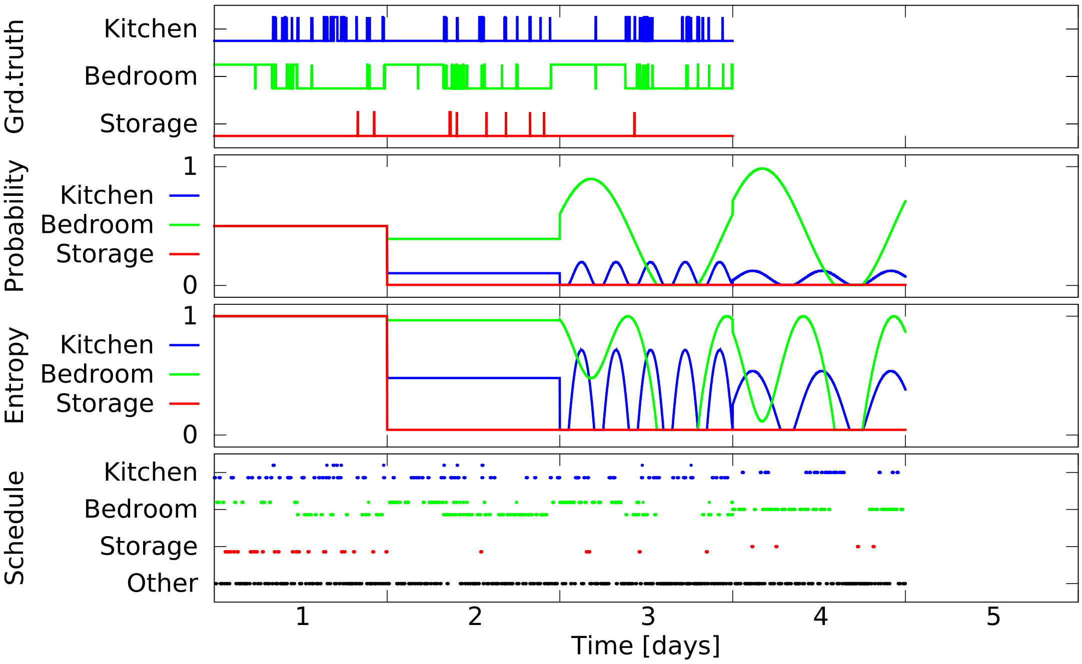


(a) Internal world model (updated based on the observation from days 1 and 2) and observation schedule for the day 3.

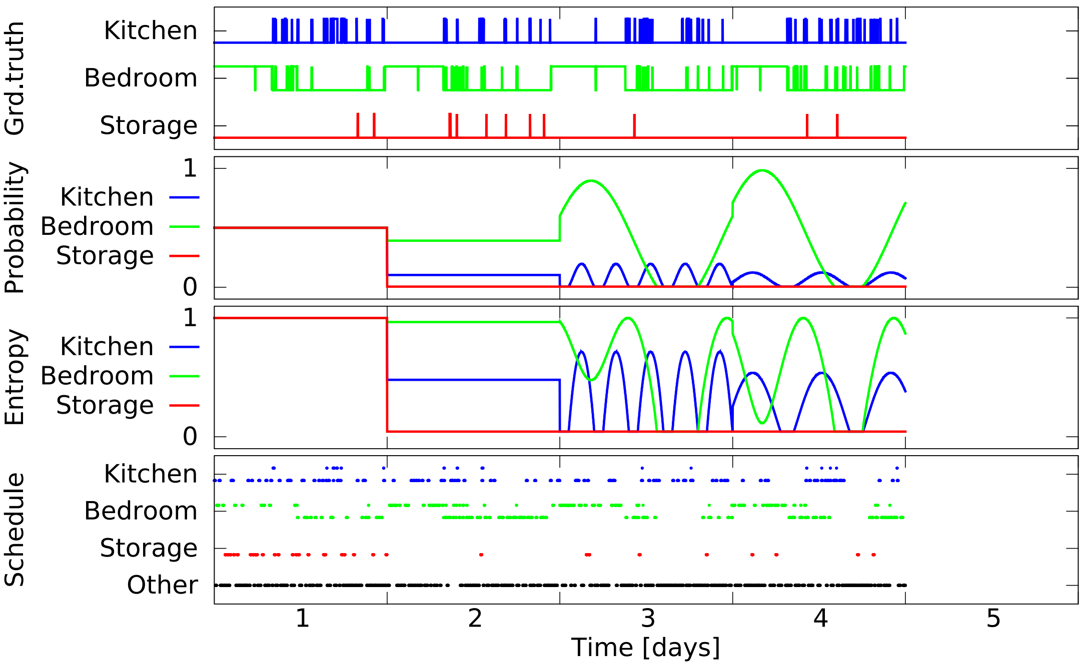


(b) Internal world model based on first 2 days observations and observation results of the first 3 days.

Figure B.3: *Internal world models, schedule and events of the first 3 days of the Aruba apartment experiment. After 2 days of observations, the robot identified daily patterns of the person presence and develops preference in observing certain locations at certain times.*

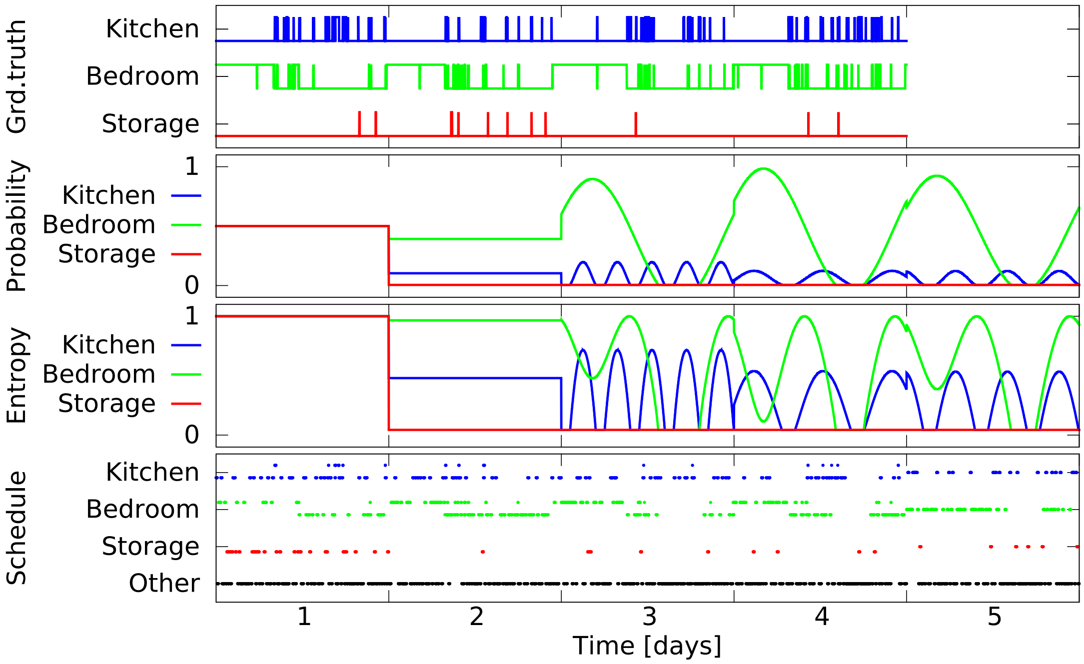


(a) Internal world model (updated based on the observation from the first 3 days) and observation schedule for day 4.

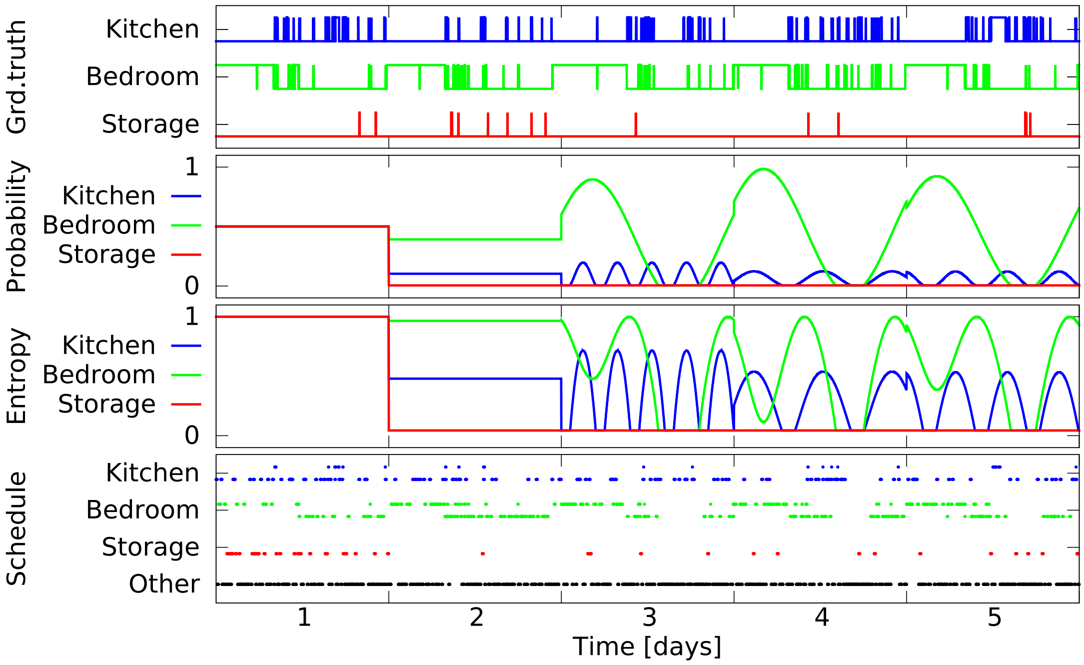


(b) Internal world model based on first 3 days observations and observation results of the first 4 days.

Figure B.4: *Internal world models, schedule and events of the first 4 days of the Aruba apartment experiment. Based on the already known daily patterns, the robot could schedule observations that allowed it to refine its spatio-temporal model of person presence.*



(a) Internal world model (updated based on the observation from the first 4 days) and observation schedule for day 4.



(b) Internal world model based on first 5 days observations and observation results of the first 4 days.

Figure B.5: *Internal world models, schedule and events of the first 5 days of the Aruba apartment experiment. The observation schedule follows closely the spatio-temporal entropy of the person presence, causing the robot to perform observations at locations and times, where the person presence is uncertain. .*