1. Now or later? Predicting and Maximising Success of Navigation Actions

Problem:

Motion planning of a robot depends highly on knowledge about the environment provided to the robot.

This knowledge gives only information about a static environment. Any real world envi is subject to change over time.

Planning success depends on robots domain knowledge. Success of navigation in a dynamic envi will be improved if these dynamic changes could be anticipated / estimated prior by the robot while planning.

Contribution:

1. the novel spectral analysis of world states gathered from robot navigation experience and the augmentation of a topological map; (ii) the study of the gathered long-term data to investigate the validity of the assumption that changes are indeed to a large extend periodic and predictions can be made; (iii) the extension of the method proposed in [2] to handle non uniform sampling and to automatically choose the best fitting model order; and (iv) the discussion and evaluation of employing this representation in high-level motion planning

Problem with the approach :

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.

2. Data-Driven Learning and Planning for Environmental Sampling

Problem

Monitoring or collecting attributes from the environment for scientific study are challenging as the attributes vary both temporally and spatially. Waypoints of the robot has to be chosen appropriately to maximize information gathered.

Challenges :

1. Selecting suitable samples which provide information gain to learn the environment dynamics. Informative planning – collecting those suitable samples

Contribution

We have developed a framework that includes two important components.

1. The first component provides a high level path planning solutions where the path/navigation waypoints.
2. Learning – hyper parameters of Gaussian process learned using Bayesian inference.
3. Dynamic Maps for long-term autonomy

*Problem*: This work focus on the problem of building a dynamic environment for robust navigation.

*Contribution*: They have presented a long-term and short-term mapping system to manage the uncertainties in the environment. They build a static map from the construction plans. To obtain a short term map, any moving obstacle like people are added to the static map. Any obstacle that continue to remain in the scene for a long period of time, are added to the long-term map.

*Problem with the contribution*: Though this long-term and short-term maps would improve the navigation, it fails to capture the dynamics of the environment. For example, if the robot observes a corridor being crowded at a particular time everyday, it might add it to the long-term map. While in reality, the corridor is crowded only during that time period of the day.

1. **Autonomous Exploration**: Information gain-based exploration using Rao Blackwellized particle filter

Problem : this work studied the problem of obtaining an accurate environmental model.

Contribution:

An information gain based approach is presented to solve the problems of exploration, mapping and localization. Their approach reduces the uncertainty in map by suitably choosing between a place re-visiting action, used for better localization and exploration action, to visit unknown areas. An entropy estimation technique is used to find the next location to explore while constructing the map. Possible future locations to observe are assessed based on the time and cost to reach.

1. Experience-based navigation for long-term localisation

Problem:

This work focus on the problem of long-term navigation in outdoor environment which changes over time.

Contribution: They have contributed to a technique which uses dynamic representation for robust localisation. When the robot visits a new location or fails to localize owing to the changes in the scene of a visited location, then those VO are saves as ‘Experience’. Each location is associated with a number of ‘Experiences’ and this number depends on the dynamic nature of the scene.

1. Meta Rooms:

Problem:

For robots navigating long term in a dynamic environment, it is essential to have an authentic model which includes dynamic information. Here the authors have tried to extract static and dynamic features from different representations of the same location.

Contribution:

They have presented a framework to separate static and dynamic parts of a dynamic environment using RGB-D scans. A meta representation containing only the static elements of the environment is built. Then the dynamic features consistently observed over time is added to the meta representation. In this work explicitly the movable objects are identified.

1. Dynamic maps for long-term operation of mobile service robots

Problem :

This work focusses on the problem of constructing a dynamic map to deal with the environment that changes with time. This map is then used for localization in a changing environment.

Contribution:

They have presented the idea of storing various representations at different timescales so that all possible changes are learnt over time. Old representations lose its importance over time. When the robot has to localize it compares its current sensor information with the past stored data and uses the one which closely matches to it.

1. Conditional Transition Map

Introduction:

stable, improves its quality over time and adapts to changes. I. I NTRODUCTION Future service robots will be required to run autonomously over really long periods of time in environments that change over time. Examples include security robots, robotic care-givers, tour guides, etc. These robots will be required to live together with people, and to adapt to the changes that people make to the world, including transient variations at different timescales (e.g., moving people, objects left temporarily, re-arranged furniture, etc.) and long-term modifications to the infrastructure of building

1. One of the biggest challenges for robotic systems which plan for delibration or navigate in a real world is to cope up with the changes

Understanding dynamic environment – key challenge for autonomous navigation.

Example scenarios :

Noticeable examples include doors being shut, stopping a robot from reaching a previously accessible place, or a crowd of people causing it to take longer to travel between two places temporarily.

these methods tackle *uncertainty at the node level of a topological map*, namely to recognise where the robot actually is. But they do not model how the transitions between nodes are affected by the dynamics of the environment.

Objective : estimate transition probabilities between the nodes

Introduction :

A service robot which would become a part of our everyday lives, should be fully autonomous. Navigation being one of the basic capability of a robot. Traditionally navigation is done by using a static map created by exploring the environment.

A robot which has a precise model of the environment is important for a robust navigation.

*Why is it relevant?*

With service robots becoming more ubiquitous, it is necessary to make them fully autonomous. A robot that not only depends on the prior information in the knowledge base but refines the knowledge over a period of time. Service robots that could operate autonomously indoor for a long period of time. Navigating autonomously in an indoor envi is more challenging due to the dynamic changes in the environment like working pattern of people existing in the environment, changes in the lighting conditions throughout the day, movable objects like door, chair and navigate in narrow, confined spaces.

Why autonomous navigation is important ?

Problems faced during autonomous navigation ?

*What is the problem?*

An indoor envi is bound to change with time. Traditional mapping techniques used ignore the dynamic changes. Generally these changes are perceived as undesirable noise and ignored.

Utilizing this dynamic changes by explicitly modeling them, can be used for better localization.

In robot navigation, without dynamic information the robot has to be more reactive and replan in case of an unanticipated obstacle on the way. Given dynamic information, the robots can choose the most efficient path to reach the goal.

Robot should be capable of learning the uncertainties about the environment over a period of time and become robust as it has more interactions with the environment.

Problem Formulation:

Why what others have done has not solved the problem ?

How are we planning to solve ?

Probabilistic modeling to quantify dynamic changes

Intelligent exploration to know when and where to observe so that the knowledge about the environment is maximized.

The robot has to explore the environment regularly as part of its regular task routine to model the spatio temporal changes in the environment.

It is not necessary for the robot to explore all the locations in equal frequencies. In order to do an efficient exploration, it is sufficient to perform observations of the locations which could improve the knowledge of the world model.