Robust SLAM In Dynamic Environments

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Abstract

SLAM is important ddddd

1 Introduction

Simultaneous localization and mapping (SLAM) is the central problem of autonomous robot navigation, and it also relates to 3-D reconstruction and augmented reality. Pose graph based SLAM approaches formulate it into an inference problem on a factor graph, where variable nodes are (unobserved) locations/poses of the robot and landmarks, and factor nodes are (observed) spatial constraints (usually Gaussians) between variable nodes. The goal of the inference problem is to obtain the maximum likelihood estimate of the joint probability, which will be the geometric estimates of robot trajectory and the map.

Problems arise when factors generated from faulty sensor data inconsistently link unrelated variable nodes, the estimated graph will be distorted. There are robust methods to deal with this, such as max-mixture[**?**] which represents factors not as a single spatial Gaussian distribution, but as a mixture of Gaussians, which can handle occasional outliers efficiently. There are also mature frameworks to efficiently optimize such estimation numerically[**?**].

Such methods mainly considers perceptual aliasing errors stemmed from wrong loop closures, and they assume landmarks to be immovable in static environments. Unfortunately such assumptions do not hold for an important application of robot navigation in social environments, where there will be people moving around, and objects moving around. If a whole block of presumed “landmarks” change their locations, max-mixture will not be able to handle the systemic errors. As far as we know, the state of art of SLAM still deals with this problem by using external filtering to avoid moving objects as a whole, a method proposed by Thrun for self-driving cars 10 years ago.

We plan to devise new graph representations and algorithms to deal with this kind of data within the factor graph framework. The baseline will be the max-mixture method. There are plenty of existing implementations and datasets to try on.

2 Related Work

related work

{mni} To gain robustness against false positive loop closures, the switchable constraints approach allows the optimizer to be able to naturally change the topological structure of the problem during the optimization itself, which significantly increases the robustness against outliers of the whole SLAM system and closes the gap between the front-end and the back-end. This way, edges representing outlier constraints can be removed from the graph during the optimization. This is achieved by augmenting the original problem and introducing an additional type of hidden variable: A switch variable is associated with each factor that could potential represent an outlier. This additional variable acts as a multiplicative scaling factor on the information matrix associated with that constraint. Depending on the state of the switch variable (a value between 0 and 1), the resulting information matrix is either the original matrix (when the switch is equal to 1) or 0 (when the switch is 0) or something between both ends. Notice that if the switch variable is equal to 0, the associated constraint is completely removed and has no influence on the overall solution.

Since in pose graph SLAM, every loop closure factor could be an outlier, we associate each loop closure edge with one of the newly introduced switch variables. With the switchable constraints, the optimization therefore works on an augmented problem, searching for the joint optimal configuration of the original variables and the newly introduced switch variables, here searching the optimal graph topology.

3 Graphical Model Formulation

The graphical model formulation of our approach is shown in figure **??**.

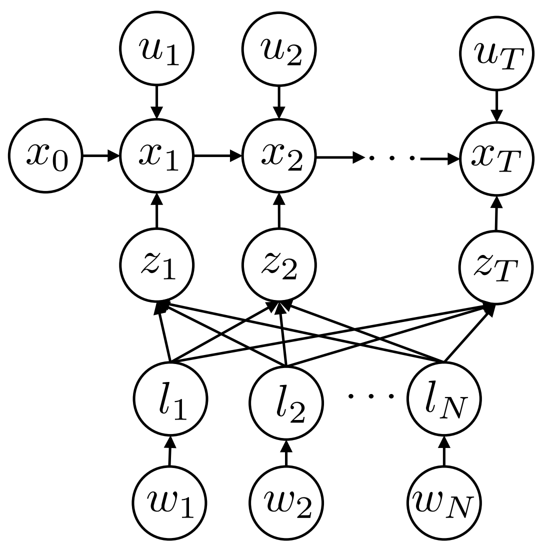

Figure 1: Graphical Model Formulation

4 Preliminary Results

prelim results.

5 Discussion

6 Timeline

Timeline for the project