A Survey on Localization with Topological Uncertainty for Autonomous Vehicle Lane Identification

ABSTRACT

For safe, effective navigation and decision-making, autonomous vehicles (AVs) require precise metric and topological location estimates. Although there are many high-definition (HD) roadmaps available, they are not always accurate because public roads are dynamic, being shaped in unpredictable ways by both human activity and nature. As a result, in this paper, AVs must be able to deal with circumstances in which the topology given by the map does not correspond to reality. The Variable Structure Multiple Hidden Markov Model (VSM-HMM) is presented as a framework for localizing in the presence of topological uncertainty, and its efficiency is demonstrated on an AV where lane membership is described as a topological localization process. VSM-HMMs use a dynamic set of HMMs to simultaneously reason about location within a set of most likely current topologies, and so may be used to estimate topological structure as well as AV lane. Furthermore, they provide an extension to the Earth Mover's Distance that allows for the inclusion of uncertainty when computing the distance between belief distributions on simplices of any relative sizes.

INDEXING- autonomous vehicles, topological location, Hidden Markov Mode

I. INTRODUCTION

Localization is a critical characteristic for autonomous mobile robotics, especially self-driving cars (AVs). As assists in the localization process, most localization algorithms employ metric maps, which represent features in continuous coordinates. Topological maps depict space as discrete components (vertices) with logical-spatial relationships (edges), where vertices and edges are defined in the graph theoretic sense. The motivating example in this study is an AV that requires a topological location estimate at the lane level in addition to a metric location estimate[1].

Because the number of unique topologies rises exponentially with the number of locations, reasoning globally about all conceivable topologies is computationally intractable. Our approach is motivated by the discrete character of topological position, as well as the desire to reason about numerous alternative realities at the same time [2]. The first fundamental notion is to use Hidden Markov Models (HMMs) for localization by modeling

predicted observations and transitions at and across topological nodes.

Three contributions are presented in this publication. First, they show how to use HMMs for lane-level localization on an AV. Second, they discuss our VSM-HMM method for managing a dynamic set of HMMs, each of which predicts a location within a distinct local topology, allowing us to lessen our reliance on high-definition (HD) maps[3]. Third, they expand the Earth Mover's Distance (EMD) to handle distributions with varying domain widths during model belief initialization.

II. RELATED WORK

Topological localization can be approached in a variety of ways. Partially Observable Markov Decision Processes can be used to describe the challenge of global topological localization (POMDP).

To reduce computational complexity, some systems directly match the robot's current perspective against representative feature vectors from topological points on the map, which eliminates most of the reasoning regarding uncertainty[4]. A number of map representations, feature extraction methods, and distance measurements, including Generalized Voronoi Graphs, SIFT and SURF features and Jeffrey divergence, have been investigated. Localization algorithms for AVs have traditionally focused on metric location, relying on high-definition (HD) maps for consistent global data association.

III. LANE IDENTIFICATION USING HMMS

Markov Chain For two main reasons, models are promising candidates for topological localization. First, HMMs are conceptually well understood and support a wide range of efficient techniques of inference. They employ the Forward algorithm in our application since it has a cheap computing cost. Second, HMMs facilitate learning and can be easily tailored to specific sensor features or topological structure[6]. Because the application of this study is lane-level localization, the states X in the HMM correspond to either being in the center of a lane or being between two lanes. HMMs' capacity to efficiently describe real-world dynamics via their transition function is a specific strength in topological localization [8]. The transition matrix defining the transition function is sparse since the AV can only travel from one lane to an adjacent lane by passing through an immediately adjacent switching state.

IV. VARIABLE STRUCTURE MULTIPLE HMMS

The Variable Structure Multiple Hidden Markov Model (VSM-HMM) is a model that is comparable to the variable-structure multiple models set of Kalman Filters that is utilized in many tracking domains[15]. If the map's suggested model has a high entropy when compared to another model, the map is most likely erroneous since high entropy suggests that no state in the suggested topology can explain the data[9]. When no information is present, the normalized equation for entropy returns equal values for all models.

However, while multiple-model techniques in the tracking and control literature anticipate the tracked object's present dynamical mode, the VSM-HMM approach evaluates the current structure of the local topology[10]. That is, rather than an internal process model, the VSM-HMM hypothesizes about the status of the outer environment. When the local topological map has non-zero uncertainty, this is required.

V. EXTENDED EARTH MOVER'S DISTANCE

When a model is first created, it requires a starting belief.

Assume an AV has an opinion, about its current topological position in a local topology[10]. is discrete and lies on the n- simplex, n, where n+1 represents the number of local topological states. In this case, n + 1 = 2L-1, where L is the number of lanes on the road down which the AV is moving.

VI. RESULTS

They do two experiments to put the VSM-HMM framework to the test. The first assesses the framework's capacity to reason about local topological structure and discover discrepancies between the map and reality, while the second assesses the framework's ability to reason about local topological structure and detect differences between the map and reality[14].

VII. CONCLUSION

Variable Structure Multiple Hidden Markov Models (VSM-HMM) are presented in this research as a framework for topological modeling. In the presence of topological uncertainty, localization is required. They show empirical results from simulated and real-world data on an autonomous vehicle that support the usefulness of VSMHMM. Future work will include using learning to automate the production and maintenance of observation and transition models, as well as combining this technique with different map representations.

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