TridentNetV2: Lightweight Graphical Global Plan Representations for Dynamic Trajectory Generation

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Abstract—We present a framework for dynamic trajectory generation for autonomous navigation, which does not rely on HD maps as the underlying representation. High Definition (HD) maps have become a key component in most autonomous driving frameworks, which include complete road network information annotated at a centimeter-level that include traversable waypoints, lane information, and traffic signals. Instead, the presented approach models the distributions of feasible ego-centric trajectories in real-time given a nominal graph-based global plan and a lightweight scene representation. By embedding contextual information, such as crosswalks, stop signs, and traffic signals, our approach achieves low errors across multiple urban navigation datasets that include diverse intersection maneuvers, while maintaining real-time performance and reducing network complexity. Underlying datasets introduced are available online.

I. INTRODUCTION

In autonomous navigation, a global plan defines the sequences of instructions needed for point-to-point navigation. These plans can be generated using various types of maps, including High Definition (HD) and Coarse maps. HD maps (e.g. nuScenes [1], Waymo Open Dataset [2], Argoverse [3], etc.) are widely used today by recent autonomous driving architectures; they provide rich contextual information such as road network definitions, lane markings, crosswalks, and drivable areas. Given that HD maps include complete road networks and lane definitions, trajectory information is readily available during path planning. This facilitates the process of identifying feasible trajectories for navigation, path tracking, and control. Nevertheless, various limitations arise in dynamic environments such as construction sites or road changes. If the environment drastically changes between the time the map was last updated and the time the autonomous agent is navigating, the agent may be unable to operate using the outdated map. A second constraint involves scalability for large scale deployments; today, most maps are labeled manually or only partially automated.

To this end, a coarse map representation for global planning can present advantages over HD maps in dynamic environments due to scalability implications; examples of coarse maps include open-source maps (i.e. OpenStreetMaps) and proprietary maps (i.e. Google Maps). These lightweight maps often include labels to describe road segments and intersections; however, lane and trajectory information is not included. This presents an open research question on identifying traversable trajectories dynamically given a scene representation.

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Fig. 1: Illustrations of global planning and scene representations for autonomous navigation: (a) trajectory generated using HD maps (blue trajectory represents plan/gray trajectories represent complete roadnetwork), (b) a trajectory generated dynamically (shown as the green trajectory) using a nominal OSM global plan and an automatically generated semantic scene representation without HD maps.

Most recently, this dynamic trajectory generation task was formulated by the TridentNet Conditional Generative Model (CGM) [4] using rasterized global plan and semantic scene representations. The approach achieves low relative errors on an urban dataset in real-world scenarios without use of HD maps. Our work extends this formulation by introducing TridentNetV2; a model that utilizes graphical global plan representations instead of rasterized representations. The graphical global plans introduced are encoded from map data extracted from OSM that includes information about road segments, crosswalks, traffic signals, and stop signs. A Self-Attention mechanism [5] is then applied to generate a global plan embedding that is then combined with a semantic scene representation. Finally, a Conditional Variational Autoencoder (CVAE) [6] is leveraged to regress feasible ego-centric trajectories that account for the multimodal nature of urban navigation. Our key contributions are as follows:

- We introduce a lightweight graph-based conditional generative model that can estimate ego-centric trajectories in real-time for the urban navigation task. In contrast to recent developments, our approach is formulated without relying on manually labeled HD maps.
- We further evaluate our formulation towards specific tasks by introducing a new dataset, IntersectionScenes1.0, specifically for intersection navigation. The
new open-source dataset is publicly available\footnote{Datasets: avl.ucsd.edu}.

- A quantitative comparison is performed with respect to a baseline model across two datasets; the approach shows improvements in terms of error reduction while reducing the model complexity by 31%.

II. RELATED WORK

A. HD maps for Autonomous Navigation

Various methodologies for autonomous navigation in urban environments have been introduced over the years. Examples of classical motion planning and control strategies that utilize HD maps include Autoware [7] and Apollo [8]. These frameworks define clear layers of abstraction for localization, perception, planning, and control modules that facilitate integration with HD maps; an example of a plan generated using HD maps is shown in Fig. 1a. Learning-based strategies have also been introduced along HD maps that bypass the layers of abstraction: examples include imitation learning [9], methods with intermediate interpretable representations [10], and mixtures of affine time-varying systems [11]. Furthermore, various mapping and road element estimation methods [12], [13], [14] have been proposed to extract environment context dynamically and reduce the reliance of expensive HD maps. In this work, we employ a probabilistic semantic mapping method [12] to provide additional semantic context besides the coarse road features provided by OSM.

B. Nominal maps and End-to-End models

Given that HD maps require high computational overhead, manual labeling, and continuous updates, methods that leverage nominal maps for navigation are of paramount interest. For this reason, learning-based strategies have utilized lightweight global plan representations to learn the distribution of potential steering control actions that an autonomous vehicle can take. For example, [15] combined rasterized OSM global plans with raw image data to learn control actions with a variational autoencoder. Similarly, [16] introduced a generative adversarial network to learn the control inputs using raw image data. Although these methods would ideally operate in unseen environments, they can suffer of severe compound errors associated with imitation learning and are trained with vehicle and sensor specific configurations. Moreover, as discussed in [17], the image-based methods are more computationally expensive. Finally, the sensor and vehicle specific representations leveraged as input features may not be applicable for new robots and different sensor configurations.

C. Dynamic Trajectory Generation

A recent research direction involves extracting visual cues from automatically generated scene representations to estimate ego-centric trajectories in real-time without depending on HD maps. In addition to operating with nominal representations, the trajectories generated are decoupled from motion planning, perception, and control. This can facilitate integration with arbitrary sensor suites and vehicle platforms without training a new model. More specifically, TridentNet CGM [4] combines a rasterized global plan representation with an aggregated probabilistic semantic scene model [12] to generate dynamic trajectories with a CVAE formulation. Although the semantic map can encode contextual information, the relationship between objects is not explicitly modeled. Thus, a compact graphical representation to model object relationships may be needed. On the other hand, Gao et al. [18] proposed using indoor maps to compute the high-level path to the goal, which are usually not accessible for general outdoor environments. Finally, [19] introduces an approach that unifies perception and planning with interpretable representations to generate plans via aggregated LiDAR scans, but the approach may not generalize for complex maneuvers that are not within the predefined driving commands including ‘keep lane,’ ‘turn left,’ and ‘turn right.’

III. GRAPHICAL REPRESENTATIONS FOR TRAJECTORY GENERATION

In this section, the method and representations used for TridentNetV2 are introduced. An overview of the model proposed is shown in Fig. 3. This approach is formulated using a global plan and automatically generated semantic maps. The global plan is represented as a graph $m_g$ which defines road connectivity and the high-level instructions needed to reach a particular destination given a GPS pose or starting point. This global plan representation serves as a coarse directional cue for the trajectory generation module. On the other hand, a local semantic representation $m_s$ describes nearby features such as drivable areas, lane markings, and sidewalks in the vehicle frame. Both representations, $m_g$ and $m_s$, are updated as part of the localization process every time a new ego-vehicle pose update is received. A CVAE approach is then applied during each update to model the distribution of potential trajectories $p(y|m)$ that can be executed by the ego-vehicle given the global plan and the semantic scene representation; where $y = \{(x_i, y_i)\}_{t=1}^H$ is the trajectory generated dynamically with a horizon $H$ and
A. Global Plan Representation

To reason about point-to-point navigation and determine if a left-turn or a right-turn is needed during intersection navigation, a global plan is needed. Previously, [20], [15], [4] applied rasterized representations that were generated using OpenStreetMaps to encode high-level information. An example can be visualized in Fig. 2a. This image-based global plan encodes the plan needed to reach a particular destination by utilizing GPS to estimate a rough pose, an IMU to estimate heading (yaw), and odometry data to update the rough vehicle state in between GPS measurements. To prevent bias towards a particular orientation or maneuver type, this global plan is represented in the ego-vehicle frame by utilizing the heading to perform a 2D rotation.

To further explore the implications of global plan representations on dynamic trajectory generation, the original global plan data from [4] is extended with graphical information (Fig. 2b). Instead of rasterizing the global plan information generated by a GPS-based planner, the plan is directly treated as a graph with feature vectors that can provide the flexibility of recent graphical methods. Afterwards, IMU-based integration is used to convert the global plan from the map frame to an ego-centric frame. In the TridentNet baseline, compounding errors are observed due to IMU-based integration. While correction procedures can be considered, our approach instead uses the trajectory information directly provided by Open Street Maps to estimate heading information. Finally, the graphical representation is augmented with additional road elements including stop signs, traffic signals, and pedestrian crossings. For the experiments described in the next section, each node within the graph \( m = \{m_g, m_s\} \) is a joint embedding for \( m_g \) and \( m_s \). These features can jointly provide detailed semantics that encode information about the scene and the global plan; thus, helping the network learn the relationship between road elements.

B. Semantic Scene Representation

Although the global plan approach using OSM can encode the high-level instructions for reaching a destination, these are low-accuracy and do not provide additional information to reason about lane markings and driveable areas. This information is needed for precise path tracking and navigation. To incorporate this contextual information, the trajectory generation model is conditioned on a local semantic scene representation \( m_s \in \mathbb{R}^{L \times L \times 3} \), where \( L = 2D \cdot L_{\text{max}}, D = 2 \) corresponds to the discretization factor in terms of pixel/m and \( L_{\text{max}} = 100m \) is the lateral and longitudinal horizon for the local semantic map (Fig. 1b). First, a 2D semantic map is generated automatically by driving once along areas of interest and is post-processed as described in [12]; the map is discretized by a factor \( D \) and is represented by an image that encodes information about driveable areas, sidewalks, crosswalks, lane markings, and vegetation. Finally, given that contextual information is only necessary for navigation within a limited horizon, we perform an \( L \times L \) region crop process at run-time by leveraging localization to perform an ego-centric coordinate transformation. This local semantic scene representation is then used as input for our model. An advantage of this approach is that it accounts for road segments with steep inclines and curved roads by leveraging camera-LiDAR projective geometry techniques.
C. Dynamic Trajectory Generation using Graphical Global Plans

A Conditional Variational Autoencoder is a deep conditional generative model [6] that implements a directed graphical model to approximate a conditional distribution \( p(y | m) \). This directed graphical method explicitly models various distribution modes by introducing a latent variable \( z \) that is drawn from the prior distribution \( p(z | m) \). An advantage of this formulation is that it can capture the multi-modal nature of a distribution, i.e., for navigation, this involves left turns, right turns, u-turns, etc. For discrete latent variables, \( z \) can be marginalized to recover the original distribution \( p(y | m) = \sum_{z \in Z} p(y | m, z) p_\theta(z | m) \). As part of the derivation, a recognition model, \( q_\psi(z | m, y) \), is introduced during training to learn a better approximation for \( p_\theta(z | m) \) since it has access to ground-truth trajectory data \( y \). The empirical objective function is then derived as follows
\[
\mathcal{L}_{cvae} = -\mathbb{E}_q[\log p_\theta(y | m, z)] + \mathbb{KL}[q_\psi(z | m, y) || p_\theta(z | m)].
\]

Motivated by the multimodal capabilities of CVAEs, we extend this formulation for dynamic trajectory generation for the urban driving scenario. Our approach follows a similar strategy as derived in [4]; however, we leverage a graphical representation to encode the global plan. Additionally, we find that by introducing a mean-squared error (MSE) loss term, lower errors can be achieved with respect to groundtruth trajectories. Thus the overall objective function that we seek to minimize is given by Eq. 1, where \( \hat{y} \) corresponds to the predicted trajectories.
\[
\mathcal{L} = \mathcal{L}_{cvae} + \frac{1}{H} \sum_{i=1}^{H} \|y_i - \hat{y}_i\|^2 \tag{1}
\]

1) Implementation: Multiple encoder modules are employed to embed the graphical representation of the global plan and the local semantic scene representation. To account for relationships across various road elements and the traversed/planned trajectories from the global plan, a Self-Attention mechanism [5] is applied within the global plan encoder. The attention operation is defined by Eq. 2 where \( C = 3 \) and \( Q, K, \) and \( V \) are linear projections of \( m_g \) that are referred to as queries, keys, and values, respectively. A multi-layer perception (MLP) is then applied to the vectorized representation of the output; thus, producing a global plan embedding \( h_g \).

\[
Attention(m_g) = m_g + \text{softmax} \left( \frac{QK^T}{\sqrt{C}} \right) V \tag{2}
\]

To encode the \( L \times L \times 3 \) tensor that describes the scene in a local frame, a sequence of convolutional and fully connected layers is applied. This semantic scene encoder generates a compressed representation \( h_s \) of the semantic model.

Lastly, the CVAE is implemented with 12 different modes (\( |Z| = 12 \)) to encode the multi-modal nature of navigation; it is assumed that \( p_\theta(z | m) \) and \( q_\psi(z | m, y) \) are categorical distributions, where \( p_\theta(z | m) \) is parameterized by concatenating \( h_g \) and \( h_s \). On the other hand, to parameterize \( q_\psi(z | m, y) \), a groundtruth trajectory feature embedding \( h_y \) is produced by applying a bi-directional LSTM; \( h_g \) and \( h_s \) are then concatenated with \( h_y \) to characterize \( q_\psi(z | m, y) \).

During training time, \( p_\theta(z | m) \) and \( q_\psi(z | m, y) \) are jointly optimized by following Eq. 1. To compute \( \log p_\theta(y | m, z) \), \( y \) is assumed to be i.i.d and \( p_\theta(y | m, z) \) is characterized by \( H \) bi-variate Gaussian distributions, namely \( \{N(\mu_i, \Sigma_i)\}_{i=1}^H \), where \( H \) corresponds to the number of waypoints that define each trajectory and Gated-Recurrent Unit (GRU) [21] is leveraged to generate \( \mu_i \in \mathbb{R}^2 \) and \( \Sigma_i \in \mathbb{R}^{2 \times 2} \) in a recurrent manner.

During testing, only the mode \( z^* \) with the highest score is sampled such that \( z^* = \arg\max_x p_\theta(z | m) \). This mode is then used to decode the predicted trajectory with the GRU.

IV. EXPERIMENTS

The data associated with these experiments is generated through the calibration, data collection, and semantic mapping process described in [12]. The groundtruth trajectories provided are automatically annotated using localization. To prevent bias towards speed, each of the trajectories is interpolated before training and extends to a 30m horizon that is characterized by \( H = 10 \) waypoints spaced 3m apart. For reference, the global plan encodes information with a precision range of approximately 1m. On the other hand, the trajectories annotated in the semantic map frame are annotated within a 2cm range.

A. Datasets

To evaluate the adopted global plan representation, the global plan data (Fig. 2a) introduced by [4] (NominalScenes1.0) is extended with its corresponding graph representation (Fig. 2b). The navigation maneuvers include lane following, three and four-way intersections, u-turns, and sharp turns. The graph information is generated based on the closest matching OSM waypoint with respect to the ego-vehicle using rough GPS estimates and the positions of the nearby nodes are rotated based on the orientation of the waypoint. This provides an OSM waypoint approximation without relying on an IMU. The dataset consists of 6,128 training and 2,864 testing samples after interpolating groundtruth poses, where each sample is composed of a global plan, a local semantic scene representation, the groundtruth trajectory, IMU data, an Unix Epoch timestamp, the state of the ego-vehicle in the semantic map frame (within 2cm precision), and its state in a global frame (in terms of latitude and longitude within 1m precision).

Secondly, a new dataset termed IntersectionScenes1.0 is introduced in this work that focuses on evaluating the performance for three-way and four-way intersection navigation. The dataset consists of 2,924 training and 1,506 testing samples after interpolation. For both datasets, the global plans are generated by a GPS-based planner that employs Dijkstra’s shortest path search algorithm and generates representations for the rasterized and graphical models. The graphical version includes stop signs, traffic signals, and pedestrian crossings as provided by OSM. For convenience,
we retain the latitude and longitude information from OSM to enable future planner implementations.

**B. Metrics**

To evaluate the performance of each of our models, we measure the quality of each trajectory generated in terms of driveable area compliance (DAC) and trajectory quality. DAC measures the ability of the model to generate trajectories that do not deviate from drivable areas; this metric is computed by an average over all trajectories that overlap with a drivable region, namely, crosswalks, lane marks, and road surfaces as defined by the local semantic map. If any trajectory waypoint overlaps with a region of sidewalk or vegetation, the prediction is strictly determined to be non-compliant. We report the error associated with half of the trajectory (DAC\(_{\text{HALF}}\)) and the complete predicted trajectory (DAC\(_{\text{FULL}}\)). Valid numerical values for compliance are given in the range \([0, 1]\).

Additionally, we leverage metrics that are commonly utilized to benchmark the performance of trajectories in road user prediction literature: Average Displacement Error (ADE) and Final Displacement Error (FDE) \([22, 23]\). By utilizing these metrics, we can examine the average error for each trajectory across all \(H\) waypoints (ADE) and the average error associated with the last waypoint predicted (FDE). An extension is performed to ADE by measuring the error associated with half of the trajectory (ADE\(_{\text{HALF}}\)) given that the waypoints closest to the autonomous agent will be executed first during navigation. Finally, the worst case errors are measured by the average maximum displacement error (MDE) along each predicted trajectory.

**C. Results**

To identify representative features for various modes of navigation, three models are introduced and compared with respect to the TridentNet CGM baseline \([4]\) that utilizes rasterized global plan representations. While all three of the studied methods utilize \((P + F) \times 3\) global plan representation, the first one (Graph-PF) only incorporates the planned and traversed trajectories, the second one (Graph-STCPF) additionally incorporates stop signs, traffic signals, and pedestrian crossings and the third model (Graph-STPF) only leverages stop signs and traffic signals in addition to the planned and traversed trajectories\(^2\).

The results for each of the models evaluated with the NominalScenes1.0 test set are shown in Table \(\text{III-A}\). It can be observed that the model that embeds stop signs and traffic signals only (STPF) outperforms the baseline and the additional graph-based methods (STCPF and PF) in terms of ADE\(_{\text{FULL}}\), FDE, and MDE. On average, the first half of each trajectory predicted (ADE\(_{\text{HALF}}\)) deviates by 35cm from groundtruth, the complete trajectory composed of \(H\) waypoints deviates by approximately 97cm from groundtruth (ADE\(_{\text{FULL}}\)), the last trajectory waypoint predicted deviates by 2.3m (FDE), and the worst waypoint prediction deviates by 2.4m (MDE). In fact, we find that the probability of a waypoint generating the worst error along a trajectory is higher at the end point than any of the previous \(H − 1\) waypoints within a trajectory by 78%.

Although the rasterized version marginally outperforms Graph-STPF in terms of ADE\(_{\text{HALF}}\), this difference may be negligible and within the localization error margin. The difference between STCPF and PF implies that by incorporating stop signs, traffic signals, and pedestrian crossings as additional node attributes, lower errors can be achieved. These road features can be relevant for distinguishing intersection navigation vs lane following. On the other hand, not all road features improve the overall performance; this becomes evident when comparing the model that uses pedestrian crossings (STCPF) and the model that does not (STPF). We suspect that the performance discrepancy occurs because crosswalk features are not exclusive to intersection navigation. In contrast to stop signs and traffic signals, crosswalks can be found during straight road segments and can potentially introduce a bias towards intersections even though an intersection does not exist.

Another interesting observation arises when evaluating the models with the DAC metrics. Although the error margin associated with half of each trajectory is minimal across most of the models, the graphical methods consistently outperform the baseline when we benchmark full trajectories. From our observations described in Section \(\text{III-A}\) we find that the failure modes associated with the baseline are often due to IMU-based integration for heading estimation and egocentric transformations. As a result, the predicted trajectories are more likely to deviate from the road if the heading is slightly off. In contrast, the graphical models use relative OSM waypoints to infer orientation and additionally incorporate information about the planned and traversed trajectory segments; thus preventing a bias towards IMU-based heading estimation. Examples with non-compliant trajectories can be visualized in Fig. \(\text{IV}\).

To further explore the strengths of incorporating stop signs and traffic signals, intersection navigation experiments are performed using the IntersectionScenes1.0 dataset. The comparison is performed specifically between STPF and the baseline model as shown in Table \(\text{III-A}\). Although it is evident...
TABLE I: A comparison between multiple graph-based global plan encoders and a raster-based encoder (baseline) evaluated on the NominalScenes1.0 dataset. ADE, FDE, and MDE error is given in terms of meters. S denotes stop signs, T denotes traffic signals, C denotes pedestrian crossings, P denotes past trajectory, and F denotes future (planned) trajectory information.

| Method           | ADE<sub>FULL</sub> | ADE<sub>HALF</sub> | FDE   | MDE   | DAC<sub>FULL</sub> | DAC<sub>HALF</sub> |
|------------------|--------------------|--------------------|-------|-------|--------------------|--------------------|
| Rasterized (baseline) | 1.056245          | 0.336941           | 2.447714 | 2.494614 | 0.849162         | 0.93218           |
| Graph-STPF        | 0.969206          | 0.353576           | 2.316740 | 2.393168 | 0.914869         | 0.944642          |
| Graph-STCPF       | 1.131581          | 0.388303           | 2.717636 | 2.795832 | 0.905864         | 0.942408          |
| Graph-PF          | 1.365685          | 0.538815           | 2.852894 | 3.047669 | 0.892321         | 0.930543          |

TABLE II: Evaluation results for intersection navigation task (IntersectionScenes1.0 dataset). ADE, FDE, and MDE error is given in terms of meters.

| Method           | ADE  | FDE  | MDE   | DAC   |
|------------------|------|------|-------|-------|
| Rasterized (baseline) | 1.793062 | 0.673450 | 3.672231 | 3.728120 |
| Graph-STPF       | 1.511415 | 0.619056 | 3.087722 | 3.226302 |

that the intersection navigation task itself is inherently more challenging than lane following which is included in Table I. The results show consistently that leveraging features that are intersection specific lead to performance improvements and can aid in generating better trajectories while entering and exiting an intersection. The multi-modal properties of our generative model can be visualized in Fig. 5 where different global plans are defined from approximately the same starting point.

V. DISCUSSION

The Self-Attention approach can encode a global plan represented as a graph without depending on IMU-based heading estimation. Compared to its rasterized counterpart that utilizes CNN layers, improvements are achieved by incorporating road features readily available from OSM. Moreover, by introducing graphical data instead of image-based tensors, the number of parameters of the model is drastically reduced by 31% as shown in Table III.

An additional consideration for robotics applications includes the real-time capabilities of the model. Given that our pose and perception information is updated at a rate of 10Hz, the processing time for the autonomy stack should remain below 100ms. All models evaluated in average have an inference time of approximately 6ms, implying that only 6% of the allotted time is utilized. Thus, the real-time characteristics of the model can provide additional flexibility for perception and decision-making modules that may require more computational time.

Additional experiments were performed with Graph Convolutional Networks [24] and LSTM-based encoders; however, performance improvements were not observed with respect to the Self-Attention model. While these results are not shown in our tables, these methods could be useful to further explore the spatial-temporal relationship as a graph by embedding complete road information over a sliding window. Nevertheless, these additional experiments demonstrate that our proposed OSM graphical representation can be applied with similar learning-based encoders.

VI. CONCLUSION

In this work, graph-based representations for global plans are studied in the context of dynamic trajectory generation without relying on HD maps. The results show that by leveraging a Self-Attention mechanism, low relative errors can be achieved with respect to the baseline composed of rasterized global plan representations whilst simultaneously reducing the complexity of generating and operating with image representations.

For future work, we plan to investigate robust methodologies for incorporating physical constraints into our generative model, apply our method as a shared mechanism for road user behavior prediction, and further investigate how to leverage real-time scene representations for dynamic trajectory generation.

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