Polyline Based Generative Navigable Space Segmentation for Autonomous Visual Navigation
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Abstract—Detecting navigable space is a fundamental capability for mobile robots navigating in unknown or unmapped environments. In this work, we treat the visual navigable space segmentation as a scene decomposition problem and propose Polyline Segmentation Variational AutoEncoder Networks (PSV-Nets), a representation learning based framework to enable robots to learn the navigable space segmentation in an unsupervised manner. Current segmentation techniques heavily rely on supervised learning strategies which demand a large amount of pixel-level annotated images. In contrast, the proposed framework leverages a generative model — Variational AutoEncoder (VAE) and an AutoEncoder (AE) to learn a polyline representation that compactly outlines the desired navigable space boundary in an unsupervised way. We also propose a visual receding horizon planning method that uses the learned navigable space and a Scaled Euclidean Distance Field (SEDF) to achieve autonomous navigation without an explicit map. Through extensive experiments, we have validated that the proposed PSV-Nets can learn the visual navigable space with high accuracy, even without any single label. We also show that the prediction of the PSV-Nets can be further improved with a small number of labels (if available) and can significantly outperform the state-of-the-art fully supervised learning based segmentation methods.

I. INTRODUCTION

For mobile robots to navigate in unknown space, it is crucial to understand the traversability of complex environments that consist of cluttered objects. The goal is to construct collision-free traversable space, which we term as navigable space. If cameras are used to perceive the environment, a typical way to identify navigable space is through image segmentation by leveraging deep neural networks (DNNs) to perform multi-class [1]–[4] or binary-class [5]–[10] segmentation of images. The present work belongs to the binary-class segmentation case where the robot needs to identify navigable space from streaming images while classifying all other parts, which are usually complex and unstructured, as non-navigable space.

However, most existing DNN-based methods are developed on top of a supervised learning paradigm and rely on annotated datasets such as KITTI [11] or CityScape [12]. These datasets usually contain an immense number of pixel-level annotated segmented images. Collecting and annotating such data for robotic applications in other environments is prohibitively costly and time-consuming, especially for outdoor environments.

To overcome the limitation of fully-supervised learning and pave a path for mobile robot navigation, we propose to develop a self-supervised learning method by treating the binary navigable space segmentation as a scene decomposition problem. It has been demonstrated in [13]–[16] that the scene decomposition can be solved in an unsupervised fashion with Variational AutoEncoders (VAEs). In contrast to semantic segmentation by supervised learning where the model is trained to learn human-annotated pixel-wise labels, scene decomposition attempts to learn the compositional nature from the visual information alone without supervision.

Most, if not all, existing VAE-based scene decomposition and representation learning methods use pixel-wise learning where the value of every pixel is predicted. However, pixel-wise approaches usually ignore dependencies between pixels, which can cause spurious holes, small scattered islands, and irregular shapes [17]. A more compact way to segment/decompose the scene is to use polylines/splines (represented by vertices or control points) to outline individual components [17], [18]. There are several benefits of using vertices-based representations. First, the number of points parameterizing the polylines is significantly less than the number of pixels in an image. Second, as shown in [19]–[21], a vertices-based representation provides an efficient and user-friendly way for possible human-machine interaction. Third, the predicted polyline is an abstract (or intermediate) representation of the environmental structure and it is shown in [22] that predictions on the intermediate representations (e.g., edges) may provide excellent clues for predicting more details, which in our case may lead to an efficient way to predict map structures.

The proposed PSV-Nets (Polyline Segmentation VAE Networks) consist of two networks, Net-I (a VAE) and Net-II (an AE). The goal of Net-I is to learn a pseudo label from surface normals by using categorical distributions as the latent representation. Using supervision signals from Net-I, Net-II learns a set of vertices which describe the location of the navigable space boundary. We then develop a navigation planning method to guide the robot to move without collision.

II. RELATED WORK

Traditional unsupervised image segmentation methods focus on crafting features and energy functions to define desired objectives. One representative framework is the active contour based models [24] which optimize over a polygon (represented by vertices) by means of energy minimization based on both the image features and some shape priors, e.g., boundary continuity and smoothness. However, active
contours lack flexibility and heavily rely on low-level image features and global parameterization of priors [25]. Recently, deep active contour based models have been proposed [25]–[28], but these methods require ground-truth contour vertices and thus belong to the supervised learning paradigm. Another line of research uses adversarial approaches for unsupervised segmentation, e.g., work in [29] explores the idea to change the textures or colors of objects without changing the overall distribution of the dataset and proposes an adversarial architecture to segment a foreground object per image. Although the adversarial methods show impressive results, they suffer from instabilities of training. This proposed research is close in spirit to some work in scene decomposition [13]–[15], where the goal is to decompose scenes into objects in an unsupervised fashion with a generative model. However, in contrast to those pixel-wise learning based approaches, our framework adopts a more compact and efficient representation – splines – to outline the boundary of the navigable and non-navigable space.

Our proposed framework is built upon VAEs. The core of VAEs is said in [30] to be well aligned with representation learning [31], which is to learn useful representations of data with little or no supervision. The trained generative model (decoder) can generate new images by taking any random samples from the learned latent distribution. Many variants of VAEs have been proposed following [32], including Conditional-VAE [33], WAE [34], Beta-VAE [35], IWAE [36], Categorical-VAE [23], joint-VAE [37], and VQVAE [38], where the latent representation could be described as either a continuous distribution, a discrete distribution, or a combination. In this paper, to learn the navigable space boundary we use two distributions for two AutoEncoders.

In addition, the value of boundaries in image segmentation has been shown in a large amount of previous literature. A polygon/spline representation is used in [18]–[21], [39] to achieve a fast and potentially interactive instance segmentation. Acuna et al propose a new approach to learn sharper and more accurate semantic boundaries [40]. By treating boundary detection as the dual task of semantic segmentation, a new loss function with a boundary consistency constraint to improve the boundary pixel accuracy for semantic segmentation is designed [41]. The work in [42] proposes a content-adaptive downsampling technique that learns to favor sampling locations near semantic boundaries of target classes. By doing so, the segmentation accuracy and computational efficiency can be well balanced. Although the above mentioned methods make use of boundaries to improve the performance, they all require ground-truth labels for training, which is an important limitation that we aim to overcome in this work.

To achieve visual navigation autonomously, learning-based methods have been widely studied recently [43], [44]. For example, imitation learning based approaches have been largely explored to train a navigation policy that enables a robot to mimic human behaviors or navigate close to certain waypoints without a prior map [45], [46]. To fully utilize the known dynamics model of the robot, semi-learning-based scheme is also proposed [44] to combine optimal control and deep neural network to navigate through unknown environments. A large amount of work on visual navigation can also be found in the computer vision community, such as [43], [47]–[50], all of which use full-learning-based methods to train navigation policies, which work remarkably well when training data is sufficient, but can catastrophically fail if no or very limited data is available.

### III. Methodology

#### A. Navigable Space Segmentation

The proposed PSV-Nets consist of two networks, as shown in Fig. 1. Net-I aims to learn a pixel-wise categorical distribution that describes the spatial layout of navigable space, whereas Net-II is designed to outline the shape of the pixel-wise prediction in Net-I using a set of vertices.

1) Net-I: The goal of Net-I is to learn a pseudo label from the input surface normal image. A standard VAE aims to learn a generative model which can generate new data from a random sample in a specified latent space. We want to obtain the parameters of the generative model by maximizing the data marginal likelihood: \( \log p_\theta(x|\tilde{x}) \), where \( \tilde{x} \) is one of data points in our training dataset \( \{ x^{(i)} \}_{i=1}^N \). Using Bayes’ rule, the likelihood could be written as:

\[
\log p_\theta(x^{(i)}) = \log \sum_z p_\theta(x^{(i)}|z)p_\theta(z),
\]

where \( p_\theta(z) \) is the prior distribution of the latent representation \( z \) and \( p_\theta(x^{(i)}|z) \) is the generative probability distribution of the reconstructed input given the latent representation. We
can use a neural network (NN) to approximate \( p_\theta(x^{(i)}|z) \) where \( \theta \) can be thought as parameters of the NN, but we cannot perform the sum operation over \( z \), hence Eq. (1) is computationally intractable.

An alternative way is to find the lower bound of Eq. (1). To derive a lower bound of Eq. (1), we can use an encoder to approximate the true posterior of latent variable \( p_\theta(z|x^{(i)}) \). We denote the encoder (another NN) as \( q_\phi(z|x^{(i)}) \), where \( \phi \) is a set of parameters of the encoder NN. Then we could derive the lower bound of Eq. (1) as:

\[
\log p_\theta(x^{(i)}) = \mathbb{E}_z \log p_\theta(x^{(i)}|z) - \mathbb{K}L(q_\phi(z|x^{(i)}))p_\theta(z) + \mathbb{K}L(q_\phi(z|x^{(i)}))p_\theta(z) \geq \mathbb{L}(\theta, \phi),
\]

where the term on the right-hand side of \( \geq \) is called the Evidence Lower Bound (ELBO) of the data marginal likelihood. Maximizing the ELBO is equivalent to maximizing the data marginal likelihood. By utilizing Monte Carlo sampling, the total loss function over the whole training dataset is:

\[
\mathcal{L}_1 = \sum_{i=1}^{N} \mathbb{K}L(q_\phi(z|x^{(i)}))p_\theta(z) + \frac{1}{2NK} \sum_{i=1}^{K} \left\| x^{(i)} - \hat{x}(z_i; \theta) \right\|_2 + \frac{J}{2} \log \sigma^2,
\]

where \( N \) is the number of images in our training dataset and \( K \) is the number of samples in Monte Carlo sampling.

2) Net-II: With the supervision signals from Net-I, Net-II can learn a set of vertices which describe the location of the navigable space boundary. We use a hybrid net consisting of a convolutional neural network and a graph convolutional network as the encoder (see the left block, E2 in Fig. 2). The overall objective of Net-II consists of a reconstruction loss and an appearance matching loss [51]. Specifically, the loss of Net-II, \( \mathcal{L}_2 \), is estimated using the Structural Similarity Index Measure (SSIM) combined with a Mean Squared Error (MSE) between \( L_1 \) and \( R_2 \),

\[
\mathcal{L}_2 = \lambda_1 \frac{1}{2} \text{SSIM}(L_1, R_2) + \lambda_2 \frac{1}{J} \left\| L_1 - R_2 \right\|_2^2,
\]

where \( J \) is the total number of pixels, \( \lambda_1 \) and \( \lambda_2 \) are weights and \( \lambda_1 + \lambda_2 = 1 \).

Specific Net-II components are described as follows.

**Image Feature Extraction (IFE):** In Net-II, the IFE module is used to extract deep features of different layers from the input image for each vertex. The coordinates of the vertices are used to pool the features at converted positions by bilinear interpolation since the sizes of different feature images are different from the original one.

**Graph Convolution Network (GCN):** We construct a graph using the vertices and use the concatenation of the extracted image features and their coordinates as the feature of each node in the graph. Our GCN structure (see Fig. 3) is inspired by the network structure proposed in recent work [21, 52]. The differences are: (a) we do not use graph unpooling layers and (b) we only use 6 graph residual convolution layers in GraphResNet. The fundamental layer of the proposed GCN module is the graph convolution layer. We denote a Graph as \( \mathcal{G} = \{ \mathcal{V}, \mathcal{E}, \mathcal{F} \} \), where \( \mathcal{V} = \{ v_i \}_{i=1}^{N} \) denotes the nodes set, \( \mathcal{E} = \{ e_j \}_{j=1}^{M} \) represents the edges set, and \( \mathcal{F} = \{ f_j \}_{j=1}^{N} \) is the feature vectors set for nodes in the graph. Then a graph convolution layer is defined as:

\[
f_{i}^{l+1} = \Gamma(w_0 f_{i}^{l} + \sum_{j \in \mathcal{N}(i)} w_1 f_{j}^{l}) = \Gamma(\mathcal{G} f_{i}^{l}),
\]

where \( f_{i}^{l+1} \) and \( f_{i}^{l} \) are the feature vectors on vertex \( i \) before and after the convolution, \( \mathcal{N}(i) \) are the neighboring nodes of node \( i \), and \( \Gamma(\cdot) \) is the activation function.

**Triangles Selection for Neural Rendering:** To convert the vertices predicted from the encoder E2 to a reconstructed image, we triangulate those vertices and select proper triangles for neural rendering. We firstly select three auxiliary vertices on the bottom boundary of image (see orange points of the left block of Fig. 2) and form a set of vertices \( \mathcal{P} \). We use Delaunay triangulation to construct triangles on \( \mathcal{P} \). Then we use neural rendering [53] to render \( \mathcal{P} \) into a mask while keeping the whole pipeline differentiable. However, a discrepancy exists: Delaunay triangulation always returns a series of triangles forming a convex hull but the shape of real navigable space is not necessarily always convex, so it is...
possible to render more triangles than needed. We propose to use a simple triangle selection method (see Fig. 3) to filter out those unnecessary triangles. In this process, we assume all the triangles are either above or under the desired navigable space boundary and no triangle crosses the boundary.

B. Visual Navigation

We achieve feasible visual navigation by combining the learned image segmentation with a receding horizon planning mechanism. Specifically, first we compute a library of motion primitives \([54], [55]\) \(M = \{p_1, p_2, \ldots, p_n\}\) where each \(p_i = \{x_1, x_2, \ldots, x_m\}\) is a single primitive. We use \(x = [x \ y \ \psi]^T\) to denote a robot pose. Then we compute the navigation cost function for each primitive based on the evaluation on collision risk and target progress. Finally we select the primitive with minimal cost to execute. The trajectory selection problem can be defined as:

\[
p_{\text{optimal}} = \arg \min_{p} w_1 \cdot C_c(p) + w_2 \cdot C_t(p),
\]

where \(C_c(p) = \sum_j c_j^c\) and \(C_t(p) = \sum_j c_j^t\) are the collision cost and target cost of one primitive \(p\), and \(w_1\) and \(w_2\) are corresponding weights, respectively.

1) Collision Avoidance: In this work, we propose a Scaled Euclidean Distance Field (SEDF) for obstacle avoidance. Conventional collision avoidance is usually conducted in the map space \([56], [57]\), where an occupancy map and the corresponding Euclidean Signed Distance Field (ESDF) have to be provided in advance or constructed incrementally in real time. In this work instead we eliminate this expensive map construction process and evaluate the collision risk directly in the image space. Specifically, we first compute a SEDF image \(E'(S)\) based on an edge map \(Edge(S)\) detected in the learned binary segmentation \(S(I)\), where \(I\) is the input image to our PSV-Nets. We then project the motion primitives from the map space to the image space and evaluate all primitives’ projections in \(E'(S)\).

To perform obstacle avoidance in image space, we have to detect the obstacle boundary in \(Edge(S)\). To achieve this, we propose to categorize the edges in \(Edge(S)\) into two classes, Strong Obstacle Boundaries (SOBs) and Weak Obstacle Boundaries (WOBs). We treat the boundary from the binary segmentation as a function of a single variable in image space, and we use the two notions of convexity and concavity of functions to define the SOBs and WOBs, respectively. SOBs mean obstacles are near to the robot (e.g.,

\[
\Omega = \{(u,v), (u,v) \in \text{Edge}(S) \land v > v_{\text{thres}}\},
\]

where \((u,v)\) are the coordinates in the image frame, as shown in Fig. 6(a) and \(v_{\text{thres}}\) is a pre-defined value for evaluating the boundary convexity. If we use \(\partial \Omega\) to denote the boundary of a set, then in our case we have \(\partial \Omega = \Omega\). Then the definition of an EDF is:

\[
E'[u,v] = \begin{cases} 
E[u,v], & \text{if } E[u,v] \leq \alpha \cdot d_{\text{max}} \\
\alpha \cdot d_{\text{max}}, & \text{otherwise}
\end{cases}
\]

where \(\alpha \in [0,1]\), and \(d_{\text{max}} = \max_{\omega \in \Omega, v \in \gamma} E[u,v]\) where \(\Omega\) and \(\gamma\) are the rows and columns index sets, respectively. Some examples of \(E'\) with different \(\alpha\) values can be seen in Fig. 6.

Assume \(x^j\) is the \(j^\text{th}\) pose in one primitive and its image coordinates are \((u^j, v^j)\), then the collision risk for \(x^j\) is

\[
c^j_t = E'[u^j, v^j].
\]
2) Target Progress: To evaluate target progress during the navigation process, we propose to use the distance on \( SE(3) \) as the metric. We define three types of frames: world frame \( F_w \), primitive pose frame \( F_{pj} \), and goal frame \( F_g \). The transformation of \( F_{pj} \) in \( F_w \) is denoted as \( T_{wpj} \), while that of \( F_g \) in \( F_w \) is \( T_{wg} \). A typical approach to represent the distance is to split a pose into a position and an orientation and define two distances on \( \mathbb{R}^3 \) and \( SO(3) \). Then the two distances can be fused in a weighted manner with two strictly positive scaling factors \( a \) and \( b \) and with an exponent parameter \( p \in [1, \infty) \) \cite{58}:

\[
d(T_{wpj}, T_{wg}) = \left[ a \cdot d_{pos}(R_{wpj}, R_{wg})^p + b \cdot d_{trans}(t_{wpj}, t_{wg})^p \right]^{1/p}.
\]

(12)

We use the Euclidean distance as \( d_{trans}(t_{wpj}, t_{wg}) \), the Riemannian distance over \( SO(3) \) as \( d_{rot}(R_{wpj}, R_{wg}) \) and set \( p \) as 2. Then the distance (target cost) between two transformation matrices can be defined \cite{59} as:

\[
c^t_j = d(T_{wpj}, T_{wg}) = \left[ a \cdot \left\| \log(R_{wpj}^{-1} R_{wg}) \right\|^2 + b \cdot \left\| t_{wpj} - t_{wg} \right\|^2 \right]^{1/2}.
\]

(13)

IV. EXPERIMENTS

A. Segmentation Performance

Datasets: We evaluate the proposed method on the standard KITTI road benchmark \cite{60}. The original data contains 289 training images (with ground-truth (gt) labels) and 290 testing images (without gt labels). Since our proposed method is designed to learn the segmentation from images in a self-supervised manner, we can only learn free space from the images without overly ambiguous boundaries such that the learned structure can be consistent with human-defined labels. Otherwise, the self-learned segmentation will be different from the gt labels (but still reasonable), causing confusion for evaluation. Therefore, throughout the experiments (including the baseline experiments), we only use the images starting with \( um \) and \( unum \) with corresponding \( road \) (instead of \( lane \)) gt labels in training data and split them into three subsets, (a) training (131 images); (b) validation (20 images) and (c) testing (40 images). We use the processed LiDAR data as the depth images and the SNE (surface normal estimation) module proposed in \cite{6} to compute the surface normal images.
method at all listed levels of gt percentages (even when 100% of the gt labels are available). A more detailed comparison can be seen in Fig. 8.

B. Planning Performance

To show the effectiveness of the proposed SEDF navigation component, we first design three maps with varying sizes in the Gazebo simulator: Env #1 (3m × 3m), Env #2 (5m × 5m), and Env #3 (7m × 7m) (map design details can be seen in the supplementary video). We randomly place cubic obstacles in the environment and the number of obstacles is proportional to the size of the map. The larger the map is, the more cluttered the environment is. Different values of α (Eq. (10)) result in different SEDF images (Fig. 6) and further affect collision avoidance during navigation. We sample 11 values of α and run 10 trials of goal-oriented (from origin to the map diagonal corner) navigation on each α value in each map, and compute the success rate (Fig. 9(a)) and the required action steps (Fig. 9(b)).

It can be seen in Fig. 9(a) that the success rate is generally proportional to the value of α, particularly when α ∈ [0.07, 0.35]. If α is too small, say < 0.07, it means the valid region of obstacle gradients is too limited (e.g., see Fig. 6(c)), thus the risk is higher for the robot to collide with obstacles, leading to a low success rate. In contrast, if the α value is too large (e.g., > 0.35), then the obstacle gradients will be propagated to the whole image and this results in a too narrow free space to navigate through (see Fig. 6(e) and Fig. 6(f)). In simulation the robot can be easily stuck during navigation especially when the environment is very cluttered. This can be seen from Fig. 9(a) that the success rate in a less-cluttered environment (e.g., Env #1) can still remain high with large α values while the rate is decreasing if the clutteredness of the environment (e.g., Env #3) is increasing.

In Fig. 9(b) we can see that the larger the environment is, the more action steps are required. It is also interesting to observe that the numbers of required action steps in all maps are also proportional to the value of α. This is because if α is small, the clearance distance to obstacles might be small while the robot passes by the obstacles to move toward the goal, thus the trajectory length might be short. On the other hand, if the value of α is large, the robot will always try to stay as far as possible from obstacles and this will cause long detours.

To further validate our proposed visual navigation system, we design a larger and more cluttered environment, as shown in Fig. 10(a) where two ending points are marked as Point #1 and Point #2. The robot will first navigate from Point #1 to Point #2 and then move in a reverse direction. The two trajectories are marked in Fig. 10(b) as Traj #1 and Traj #2, respectively. Demonstrations are provided as supplementary materials.

V. CONCLUSION

We propose a new framework, PSV-Nets, to learn the navigable space in an unsupervised fashion. The proposed framework discretizes the boundary of navigable spaces into a set of vertices. We then present a local navigation planning framework to guide the robot to navigate with the output of PSV-Nets. With extensive evaluations, we have validated the effectiveness of the proposed method and the remarkable

![Fig. 8.](image) Quantitative results on KITTI road benchmark. The horizontal axis represents the percentage of the used gt labels (only the data of 4 percentages are shown: 0, 1, 30, and 100). The statistical results are computed from all of the 40 images in testing data.

![Fig. 9.](image) Navigation behaviors comparison with different values of α in multiple maps.

![Fig. 10.](image) Navigation in a cluttered room environment with random furniture. Demonstrations are provided in the supplementary video.
advantages over the state-of-the-art fully supervised learning baseline method.

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