Classification and Embedding of Semantic Scene Graphs for Active Cross-Domain Self-Localization

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Abstract: In visual robot self-localization, semantic scene graph (S2G) has attracted recent research attention as a valuable scene model that is robust against both viewpoint and appearance changes. However, the use of S2G in the context of active self-localization has not been sufficiently explored yet. In general, an active self-localization system consists of two essential modules. One is the visual place recognition (VPR) model, which aims to classify an input scene to a specific place class. The other is the next-best-view (NBV) planner, which aims to map the current state to the NBV action. We propose an efficient trainable framework of active self-localization in which a graph neural network (GNN) is effectively shared by these two modules. Specifically, first, the GNN is trained as a S2G classifier for VPR in a self-supervised learning manner. Second, the trained GNN is reused as a means of the dissimilarity-based embedding to map an S2G to the fixed-length state vector. To summarize, our approach uses the GNN in two ways: (1) passive single-view self-localization, (2) knowledge transfer from passive to active self-localization. Experiments using the public NCLT dataset have shown that the proposed framework outperforms other baseline self-localization methods.

1 INTRODUCTION

Cross-domain visual robot self-localization is the problem of predicting the robot pose from on-board camera image using an environment model (e.g., map), which was previously trained in different domains (e.g., weathers, seasons, times of the day). A large body of self-localization literature focuses on designing or training the models that are robust to changes in appearance and viewpoint. Most of them assume a single-view self-localization scenario and do not consider viewpoint planning or observer control issues. However, such a passive self-localization problem is essentially ill-posed when current live images are from a previously unseen domain. Existing solutions can be negatively influenced by environmental and optical effects, such as occlusions, dynamic objects, confusing features, illumination changes, and distortions. One promising approach to address this issue is to consider an active self-localization scenario (Gottipati et al., 2019), in which an active observer (i.e., robot) can adapt its viewpoint trajectory, avoiding non-salient scenes that provide no landmark view, or moving efficiently towards places which are most informative, in the sense of reducing the sensing and computation costs. This

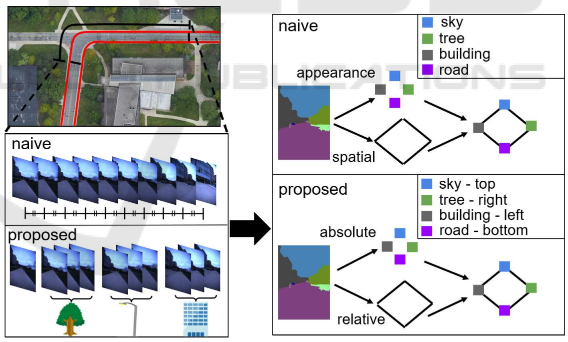

Figure 1: The nodes and edges in a semantic scene graph represent the absolute attribute of an image region and the relative attribute between a region pair, respectively.

is most closely related to the next-best-view (NBV) problem studied in machine vision literature. However, in our cross-domain setting, a difficulty arises from the fact that the NBV planner is trained and tested in different domains. Existing NBV methods that do not take into account domain shifts would be confused and deteriorated by the domain-shifts, and require significant efforts for adapting them to a new domain.

In this work, we present a novel framework for active cross-domain self-localization based on the se-

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mantic scene graph (S2G), as shown in Fig. 1. In general, an active self-localization system consists of two essential modules (Gottipati et al., 2019):

(1) Visual place recognition (VPR) model, to classify an input scene to a specific place class;

(2) Next-best-view (NBV) planner, to map the current state to the next-best-view action.

We are motivated by recent findings that S2G is a valuable scene model that is robust to both viewpoint and appearance changes (Gawel et al., 2018). In our approach, a trainable S2G classifier is effectively shared by these two modules. Specifically, first, a graph neural network (GNN) is trained as the VPR module in a self-supervised learning manner. Second, the trained GNN is reused as an S2G embedding model to transfer the state recognition ability of the trained GNN to the NBV planner module. Experiments using the public NCLT dataset (Carlevaris-Bianco et al., 2016) have shown that the GNN classifier based on the semantic scene graph outperforms other baseline self-localization methods. It was also shown that the proposed dissimilarity-based graph embedding generates good NBV action plans in the NBV planning task.

2 RELATED WORK

2.1 Cross-Domain Self-Localization

Self-localization under changes in viewpoint and appearance is a challenging problem, and has been extensively studied (Lowry et al., 2016; Garg et al., 2021; Zhang et al., 2021). Early works explored local feature based self-localization approaches such as bag-of-words (Cummins and Newman, 2011), in which a query/map image is described by a collection of local visual features. However, such a local feature approach ignores contextual information (e.g., spatial information) of the entire image, and is vulnerable to changes in appearance caused by weather or seasonal changes. To address this issue, some works employ global features to improve robustness against appearance changes. For example, GIST (Oliva and Torralba, 2001), a representative global feature, uses a fixed-length feature vector to precisely describe and match the contextual information of the entire image. However, since global features depend on the information of the entire image, they are vulnerable to viewpoint changes. Recently, attempts have been made to improve the discriminative power of local and global features using deep learning techniques (Zhang et al., 2021). However, the vulnerability to change is inherent in local and global visual features and has not been overcome yet.

2.2 Semantic Scene Graphs

In recent years, semantic scene graphs (S2G) have attracted attention from researchers as a robust self-localization method under both appearance and viewpoint changes (Gawel et al., 2018). A semantic scene graph is an attributed graph whose nodes and edges describe semantically attributed image regions and relationship between them. Many studies have formulated the S2G-based self-localization as a graph matching problem (Kong et al., 2020). For example, the X-View method in (Gawel et al., 2018) employs a graph matching algorithm based on random walk to obtain improved robustness under appearance and viewpoint changes. However, graph matching techniques rely on structured pattern recognition algorithms, and thus suffer from increasing computation cost. On the other hand, graph embeddings have gained attention as a way to reduce the costly graph matching problem to an efficient machine learning problem (Cai et al., 2018). However, its preprocessing typically requires supervised learning of a graph embedding model, which limits its applicability to autonomous mobile robots. Recently, graph neural network (GNN) has emerged as a means of machine learning directly on general graph data without requiring graph embedding. This has motivated us to use the GNN classifier as a method for visual place classifier.

2.3 Graph Embedding

The graph embedding formulation considered in our study is most closely related to the dissimilarity-based graph embedding scheme, one of representative graph embedding approaches in the field of computer vision and pattern recognition (Borzeshi et al., 2013). The dissimilarity-based embedding aims to describe an input graph by its dissimilarity to a set of predefined prototype graphs. However, the choice of dissimilarity measure is application dependent and no general solution exists. Some methods employ graph edit distance as a means of dissimilarity measure (Wang et al., 2021). However, such a structured pattern recognition algorithm suffers from high computational cost. Several recent works attempt to train efficient graph embedding models by deep learning. However, they follow a supervised learning protocol and require costly supervision, which is not available in our autonomous robot applications. In contrast, our approach reuses the pre-trained passive GNN classifier as the dissimilarity model. This approach is appealing in terms of training efficiency and real-time performance. Specifically, the GNN classifier can be a novel computationally-efficient dissimilarity measure, because it does not require costly structured-pattern recognition nor supervised graph embedding networks.

2.4 Next-Best-View Planners

Several researchers have studied the problem of next-best-view planning for active robot self-localization. In (Burgard et al., 1997), an active self-localization task was addressed by extending the Markov localization framework for action planning. In (Feder et al., 1999), an appearance-based active observer for a micro-aerial vehicle was presented. In (Chaplot et al., 2018), a deep neural network-based extension of active self-localization was addressed using a learned policy model. In (Gottipati et al., 2019), the policy model and the perceptual and likelihood models were completely learned. In (Chaplot et al., 2020), a neural network-based active SLAM framework was investigated. However, these existing studies suppose in-domain scenarios, where the changes in appearance and viewpoint between the training and test domains was not significant. The availability of domain-invariant landmarks was often assumed (e.g., (Tanaka, 2021)). In contrast, in our work, the challenging cross-domain active self-localization scenario is addressed by utilizing a deep graph neural network in two ways: passive self-localization (i.e., visual place recognizer) and active self-localization (i.e., next-best-view planner).

2.5 Relation to Existing Works

To our knowledge, this work is the first to study semantic scene graph (S2G) in the challenging scenario of active cross-domain self-localization. Existing machine learning approaches require as input fixed-length feature vectors such as local and global features. However, they had the limitation of being vulnerable to changes in viewpoint and appearance. Our approach employs a new scene model, the semantic scene graph (S2G), which is robust to both types of change. However, S2G is no longer a fixed-length feature vector, and thus cannot be dealt with by most machine learning frameworks. The graph neural network (GNN) used in our research is a valuable recently emerging machine learning framework that can directly process graph data. Moreover, we explore to reuse the trained GNN as a means of embedding an S2G to a fixed vector, which is then used as the discriminative state vector for training the viewpoint planner. Consequently, in our approach, GNNs are utilized not only as passive S2G classifiers, but also as a means of knowledge transfer from passive to active self-localization.

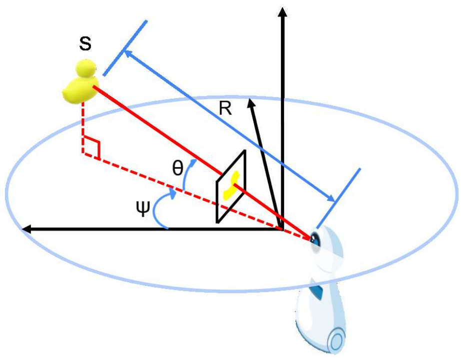


Figure 2: Bearing-range-semantic (BRS) measurement model. The bearing, range, and semantics are observed in an image, as the location, area, and semantic label, respectively, of an object region. Then, the three-dimensional B-R-S space is quantized to obtain a compact 189-dim 1-hot vector (i.e., an 8-bit descriptor).

3 APPROACH

The proposed framework consists of two main modules: (offline) training module and (online) test module. In addition, a scene graph descriptor sub-module is employed by the both modules. These modules are detailed in the following subsections.

3.1 Semantic Scene Graph

We employ a simple bottom-up procedure for scene parsing, to generate a semantic scene graph from a given query/map image. First, semantic labels are assigned to pixels using DeepLab v3+ (Chen et al., 2018), which was pretrained on Cityscapes dataset. Then, regions smaller than 100 pixels are regarded as not characterizing the input scene, and removed. Subsequently, connected regions with the same semantic labels are identified using a flood-fill algorithm (He et al., 2019), and each region is assigned a unique region ID. Next, each region is connected to each of its adjacent regions by a graph edge. As a result, a semantic scene graph with the nodes and edges described above is obtained.

We observe that not only semantic information but also spatial information is important in the robotic applications. This spatial information is particularly important in the SLAM field, and existing SLAM frameworks are classified into several categories ac-

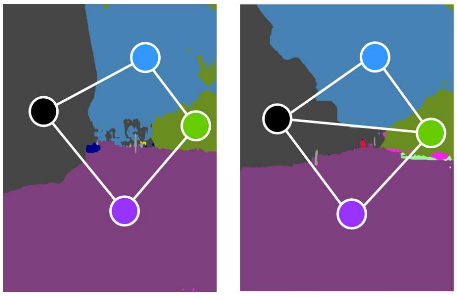


Figure 3: Using edges enables to distinguish between two similar but different scene layouts, as in this example.

cording to the type of spatial information, such as range-bearing SLAM (Ramezani et al., 2020), range-only SLAM (Song et al., 2019), and bearing-only SLAM (Bj et al., 2017). Our problem formulation falls into an alternative category of bearing-range-semantic (BRS) -based self-localization (Fig. 2).

Specifically, in our approach, a semantic scene graph is computed in the following procedure. First, the semantic labels output by a semantic segmentation network in (Ronneberger et al., 2015) were re-categorized into seven different semantic category IDs: "sky," "tree," "building," "pole," "road," "traffic sign," and "the others" which respectively correspond to the labels {"sky"}, {"vegetation"}, {"building"}, {"pole"}, {"road," "sidewalk"}, {"traffic-light," "traffic-sign"}, and {"person," "rider," "car," "truck," "bus," "train," "motorcycle," "bicycle," "wall," "fence," "terrain"} in the original label space. The location of the region center was quantized into nine "bearing" category IDs by a 3×3 regular grid imposed on the image frame. Area of the region was quantized into three "range" category IDs: "short distance (larger than 150 K pixels)," "medium distance (50 K-150 K pixels)," and "long distance (smaller than 50 K)" for 616×808 image. Finally, these semantic, bearing and range category IDs are combined to obtain a (7×3×9=) 189-dim 1-hot vector as the node descriptor.

We observe that the nodes and edges represent two different aspect of the spatial information, which can act as error detection codes (Córcoles et al., 2015) that complement each other. Specifically, an edge is suitable for describing the relative feature (e.g., position-relationship), while a node is suitable for describing the absolute feature (e.g., position). Figure 3 illustrates an example showing how the use of edge information helps to discriminate a near-duplicate scene pair, which the node descriptor alone could not discriminate.

We also adopted a region merging technique, inspired by a recent work in (Matejek et al., 2019). Specifically, we remove regions smaller than 1,000 pixels (for 616×808 image). We noted this simple technique to be quite effective in improving self-localization performance.

3.2 Visual Place Recognition

Self-localization from semantic scene graph is directly addressed by graph convolutional neural network (GCN) (Wang et al., 2019) -based visual place classifier. GCN is one of most popular approaches to graph neural networks. Specifically, we aim to train a GCN as a visual place classifier, which takes a single-view image and predicts the place class.

For the definition of place classes, we follow the grid-based partitioning in (Kim et al., 2019). In the experimental environment, this yields 10×10 grid cells and 100 place classes in total.

In this study, a GCN is trained by using the semantic scene graphs as the training data. The graph convolution operation takes a node v_i in the graph and processes it in the following manner. First, it receives messages from nodes connected by the edge. The collected messages are then summed via the SUM function. The result is passed through a single-layer fully connected neural network followed by a nonlinear transformation for conversion into a new feature vector. In this study, we used the rectified linear unit (ReLU) operation as the nonlinear transformation. The process was applied to all the nodes in the graph in each iteration, yielding a new graph that had the same shape as the original graph but updated node features. The iterative process was repeated L times, where L represents the ID of the last GCN layer. After the graph node information obtained in this manner were averaged, the probability value vector of the prediction for the graph was obtained by applying the fully connected layer and the softmax function. For implementation, we used the deep graph library (Wang et al., 2019) on the Pytorch backend.

In the multi-view self-localization scenario, the latest viewimage/odometry measurement at each time is incrementally fused into the belief state. For the information fusion, the standard Bayes filter-based information fusion as in (Dellaert et al., 1999) is adopted. The motion and perception models of the Bayes filter are adopted to our specific application domain. Specifically, a motion corresponds to a forward move along the viewpoint trajectory, and a perception corresponds to a class-specific probability density vector (PDV) output by the GCN. In implementation, a slightly simplified motion and perception models are used. First, the marginalization step associated with the robot motion model was skipped by utilizing a noise-free motion model. Then, the Bayes rule step associated with the robot perception model was replaced with a reciprocal rank fusion operation in (Cormack et al., 2009).

The spatial resolution of the Bayes filter state space (e.g., 1 m) is required to be the same or higher than that of the odometer sensor, which is much higher than that of the state space of visual place classifier. Conversion between two state vectors with such different spatial resolutions is simply implemented as a marginalization operation.

3.3 Next-best-View Planning

The next-best-view planning is formulated as a reinforcement-learning (RL) problem, in which a learning agent interacts with a stochastic environment. The interaction is modeled as a discrete-time discounted Markov decision process (MDP). A discounted MDP is a quintuple (S,A,P,R,γ), where S and A are the set of states and actions, respectively. P denotes the state transition distribution, R denotes the reward function, and $\gamma \in (0,1)$ denotes a discount factor ($\gamma = 0.9$). The learning rate was set to $\alpha = 0.1$. We denoted $P(\cdot|s,a)$ and $r(s,a)$ as the probability distribution over the next state and the immediate reward of performing an action a for a state s, respectively. Specifically, the state s is defined as the class-specific reciprocal rank vector, output by the GCN classifier. The action a is defined as a forward movement along the route.

In the experiments, we use a specific implementation as shown below. The action set is a size 10 set of candidates of forward movement along the predefined trajectories $A = \{1, 2, \cdots, 10\}$ (m). Each training/test episode is a length $n = 4$ perception-plan-action sequence. The RL is trained by the recently developed efficient RL scheme of nearest neighbor Q-learning (NNQL) (Shah and Xie, 2018) with neighborhood factor $k = 4$. The immediate reward is provided at the final viewpoint of each training episode, as the reciprocal rank value of the ground truth place-class.

4 EXPERIMENTS

The proposed method was evaluated in an active cross-domain self-localization scenario. The goal of the evaluation was to validate whether the GCN-based classifier and embedding of semantic scene graph could boost the performance in both the passive and active self-localization modules.

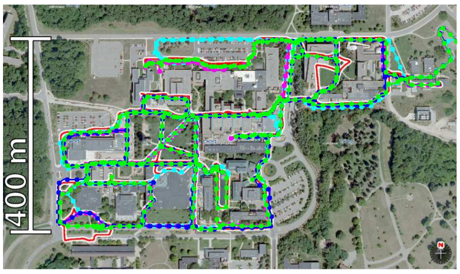


Figure 4: Experimental environments. The trajectories of the four datasets, “2012/1/22,” “2012/3/31,” “2012/8/4,” and “2012/11/17,” used in our experiments are visualized in green, purple, blue, and light-blue curves, respectively.

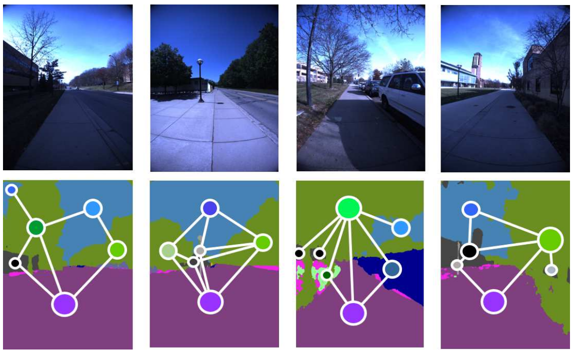
4.1 Dataset

The public NCLT long-term autonomy dataset (Carlevaris-Bianco et al., 2016) was used in the experiments (Fig. 4). The dataset was collected through multi-session navigation under various weather, seasons and times of day over multiple years using a Segway vehicle at the University of Michigan North Campus. While the vehicle travels seamlessly indoors and outdoors, the vehicle encountered various geometric changes (e.g., object placement changes, pedestrians, car parking/stopping) and photometric changes (e.g., lighting conditions, shadows, and occlusions).

In particular, we supposed a challenging cross-season self-localization scenario, in which the self-localization system is trained and tested in different seasons (i.e., domains). Specifically, four seasons’ datasets “2012/1/22 (WI),” “2012/3/31 (SP),” “2012/8/4 (SU),” and “2012/11/17 (AU)” were used to create four different training-test seasons pairs: (WI, SP), (SP, SU), (SU, AU), and (AU, WI). Additionally, an extra season “2012/5/11 (EX)” was used to train the visual place classifier. That is, the classifier was trained only once in the season EX, prior to the self-localization tasks, and then the learned classifier parameters were commonly used for all the training-test season pairs. The number of training and test episodes were 10,000 and 1,000, respectively.

4.2 Comparing Methods

Three different self-localization methods, GCN, naive Bayes nearest neighbor (NBNN), and k-nearest neighbor (kNN) were evaluated. The GCN is the proposed method that uses GCN in two ways, VPR and NBV from a semantic scene graph (S2G), as described in Section 3. Other comparing methods are non-S2G-based methods, which ignore graph edges and represent an input image as a collection of image



(a) (b) (c) (d)

Figure 5: Examples of semantic scene graph. Top: The input scene. Bottom: The corresponding scene graphs overlaid on the semantic label image.

regions. For fair comparison, the same node regions used in the proposed method were used as the image regions in the comparing methods. NBNN and kNN methods are based on measuring dissimilarities in the node feature set between a query-map pair of interest. NBNN (Tommasi and Caputo, 2013) is one of the best known methods to measure dissimilarities between such a feature set pair. In that, the L2 distance from the nearest-neighbor map feature to each query feature is computed, and then it is averaged over all the query features, which yields the NBNN dissimilarity value. kNN is a traditional non-parametric classification method based on the nearest-neighbor training sample in the feature space, in which the class labels most often assigned to the training samples of the kNN (i.e., minimum L2 norm) are returned as classification results. In that, an image is described by a 189-dim histogram vector by aggregating all the node features that belong to the image.

4.3 Performance Index

Self-localization performance was evaluated in terms of top-1 accuracy. The evaluation procedure was as follows. First, self-localization performance at all viewpoints of the query episode, and not just the final viewpoint, were computed. Then, top-1 accuracy at each viewpoint was computed from the latest Bayes filter output based on whether the class with highest belief value matches the ground-truth.

4.4 Results

Figure 5 shows semantic scene graphs used in the experiments. Notably, the domain-invariant scene parts (e.g., buildings and roads) of the input scenes tended to be selected as the dominant parts.

Figure 6 shows examples of views before and after

(a) (b) (c) (d)

Figure 6: Next-best-view planning results. In each figure, the bottom and top panels show the view image before and after the planned next-best-view actions, respectively.

Table 1: Performance results.

"RM": region merging, "S": semantic, "BRS": bearing-range-semantic, "VPR": visual place recognition (w/ random action planning), "VPR+NBV": VPR w/ next-best-view planning

		w/ RM		w/o RM	
		S	BRS	S	BRS
VPR	GCN	11.7	**18.9**	12.0	19.1
	kNN	5.8	15.6	6.3	12.9
	NBNN	1.3	3.4	1.4	3.5
VPR+NBV	GCN	19.9	**31.4**	19.5	32.3
	kNN	10.9	28.4	11.2	24.8
	NBNN	2.2	4.7	2.7	4.6

planned next-best-view actions. Intuitively convincing behavior of the robot was observed. Before the move, the scene was a non-salient one consisting only of the sky, the road, and the trees (Fig. 6 a,b,c), or the field of view was very narrow due to occlusions (Fig. 6d). After the move, landmark objects came into view (Fig. 6 a,c) or additional landmarks appeared (Fig. 6 b,d). Such behaviors are intuitively appropriate and effective for seeking and tracking landmarks when a human becomes lost and looks for familiar landmark objects. Our approach enables the robot to learn such an appropriate state-to-action mapping from available visual experience.

Series of experiments were conducted to observe the effects of individual components, including the graph edges and the region merging. Table 1 lists the results of the proposed next-best-view planner ("VPR+NBV") and a baseline planner with random action planning ("VPR"). Moreover, we compared the proposed BRS-based region descriptor ("BRS") with the baseline semantic label-based region descriptor ("S"). Notably, the proposed method yielded a superior performance compared to the other methods. The technique of region merging contributed to reduce the number of nodes while retaining the self-localization performance. The number of nodes was reduced from 19.8 to 7.2 per semantic scene graph on

Table 2: Ablation studies.

Training-Test	SP-SU	SU-AU	AU-WI	WI-SP
BRS regions	23.8	14.8	15.3	21.7
BRS image	21.4	13.9	13.7	20.1
B-R-S regions	20.1	12.2	13.7	19.2

average, which results in the reduction of computation time for self-localization from 0.82 ms to 0.16 ms. Particularly, the use of edge feature and the next-best-view planner often significantly boosted the self-localization performance.

Table 2 lists the results of additional ablation studies. Here, we verified the importance of graph topology and region descriptors. In the table, “BRS regions” and “B-R-S regions” use semantic scene graphs based on segmentation, but have different descriptors for region nodes. “BRS regions” is the proposed method that represents region nodes by a 1-hot vector in the discretized joint space of bearing range semantics. “B-R-S regions” is an alternative method that first computes 1-hot vectors independently in each of the three discretized spaces of bearing, range, and semantics, and then concatenate the three 1-hot vectors to obtain a 3-hot state vector (“B-R-S regions”). “BRS image” differs from “BRS regions” only in terms of graph topology, and uses a single-node semantic scene graph with the entire image as a graph node. From this table, we can see that the proposed method, which describes the semantic scene graph consisting of region nodes using 1-hot region descriptors of the BRS joint space, outperforms the other methods.

We observe that the descriptor compactness is quite important in the training phase because the reinforcement learning procedure iterates the classification process for hundreds of thousands of times through the training episodes. In our approach, sufficiently compact scene descriptor was acquired by the proposed approach, as shown bellow. The number of nodes per semantic scene graph was 7.2 on average. The node descriptor consumed 8-bit per node. The space cost for nodes and edges were 57.8-bit and 12.5-bit per semantic scene graph, respectively, on average. This a low space cost, even compared to the most compact existing descriptors such as bag-of-words. Notably, the current descriptors were not compressed, i.e., they may be further compressed.

5 CONCLUDING REMARKS

In this paper, a new trainable framework for active cross-domain self-localization by using the semantic scene graph model is presented. In the proposed framework, graph neural networks (GNNs) are used in two ways. First, the GNN is trained as a visual place classifier for passive single-view self-localization in the fashion of self-supervised learning. Second, the trained GNN is reused as a means of embedding S2G into a fixed-length state vector, which is then fed to the reinforcement learning module to train the next-best-view planner. Experiments showed that the proposed method is effective in both passive self-localization and knowledge transfer from passive to active self-localization. The proposed framework was found to be robust to changes in both viewpoint and appearance. In the future, we plan to clarify these robustness and limitations through further research using real robots as well as simulated environments.

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