Domain-invariant NBV Planner for Active Cross-domain Self-localization

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Abstract—Pole-like landmark has received increasing attention as a domain-invariant visual cue for visual robot self-localization across domains (e.g., seasons, times of day, weathers). However, self-localization using pole-like landmarks can be ill-posed for a passive observer, as many viewpoints may not provide any pole-like landmark view. To alleviate this problem, we consider an active observer and explore a novel “domain-invariant” next-best-view (NBV) planner that attains consistent performance over different domains (i.e., maintenance-free), without requiring the expensive task of training data collection and retraining. In our approach, a novel multi-encoder deep convolutional neural network enables to detect domain invariant pole-like landmarks, which are then used as the sole input to a model-free deep reinforcement learning-based domain-invariant NBV planner. Further, we develop a practical system for active self-localization using sparse invariant landmarks and dense discriminative landmarks. In experiments, we demonstrate that the proposed method is effective both in efficient landmark detection and in discriminative self-localization.

I. INTRODUCTION

Cross-domain self-localization is the problem of estimating a robot pose given a history of sensor readings including visual images/odometry data, with respect to an environment map that was previously collected in different domains (e.g., weathers, seasons, times of the day). A large body of self-localization literature focuses on designing or training a landmark detector that is robust against domain shifts [1]–[3]. However, the problem of designing/training such a domain-invariant landmark detector 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 utilize inherently invariant landmark objects that are stable and visually invariant against domain-shifts, such as walls [4], roads [5], and poles [6]. In this study, we are particularly interested in the use of pole-like landmarks because they are ubiquitous both in indoor and outdoor environments.

Thus far, most of previous works on self-localization suppose a passive observer (i.e., robot), and do not take into account the issue of viewpoint planning, or controlling the observer. However, the pole-like landmark-based self-localization can be ill-posed for a passive observer, as many viewpoints may not provide any pole-like landmark view. Therefore, we consider an active self-localization task that can adapt its viewpoint trajectory, avoiding non-salient scenes that provide no pole-like landmark view, or moving efficiently towards places which are most informative, in the sense of reducing the sensing and computation costs. This is most closely related to the next-best-view (NBV) problem studied in machine vision literature [7]. 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 propose a novel class of NBV planner, termed “domain-invariant” NBV planner (Fig. 1), that attains consistent performance over different domains, without requiring the expensive task of training data collection and
retraining (i.e., maintenance-free). The domain-invariance can be considered as a novel advantage of the proposed approach to existing NBV planners. Intuitively, a domain-invariant NBV planner could restrict itself to take domain-invariant visual features as the sole input. In addition, it could learn domain-invariant statistics of landmark configuration, such as average travel distance between pole-like landmark views. Moreover, it could arrange the plan depending on whether the current live image is a landmark view or not. However, training a domain-invariant landmark detector as well as an NBV planner, with reasonable computational cost, from an available visual experience, is a non-trivial problem and which is the focus of our study.

We tackle this problem by introducing a deep convolutional neural network (DCN) -based landmark detector and a deep reinforcement learning (DRL) -based NBV planner. Our DCN module is built on a recently developed multi-scale multi-encoder deep convolutional neural network [8]. Our formulation of DRL is related to recent works on deep reinforcement learning -based NBV planner [9]. However, rather than using typical sensor inputs such as raw images, we propose to use domain-invariant perceptual information, which is made available by the proposed landmark detector, to make our NBV planner a domain-adaptive one.

Our main contributions are summarized as follows: (1) This work is the first to address the issue of domain-invariant NBV using invariant pole-like landmarks. (2) Our landmark detection network is built on the recent paradigm in image edge detection, deep holistic edge detection (HED), which can detect a small number of holistic essential scene structure, rather than conventional detectors such as Canny [10] that tend to detect lots of complex primitive edges. (3) The effectiveness of the planning algorithm in terms of self-localization performance and domain-invariance is verified via experiments using publicly available NCLT dataset.

II. Problem

Active self-localization task consists of four distinctive stages: planning, action, detection, and matching (Fig. 2). The planning stage determines the NBV action, given a history of live images and states, using an NBV planner that is trained in a past domain. The action stage executes the planned NBV action. The detection stage aims to detect domain-invariant landmark objects using the pre-trained detector. The matching stage aims to query a pre-built database of landmark views associated with ground-truth GPS viewpoints to infer the robot pose, and this stage is performed only when one or more landmark objects are detected. The inference result and all the inference history from previous iterations are integrated to obtain an estimate of the robot pose and its confidence score. The above four stages are iterated until the confidence score exceeds a preset threshold.

III. Approach

This section presents the proposed framework for active visual self-localization (Fig. 3). The domain-invariant pole-like landmark detection network (PLD), as well as the domain-adaptive action policy determination block (APD), are emphasized. On the other hand, spatial landmark aggregation module (SLA) can reduce the dimension of PLD output and computational complexity of the DRL -based learner/planner. On the other hand, through fusing invariant pole-like landmarks and discriminative holistic edge images, the passive self-localization block (PSL) can make use of the information from PLD. One the other hand, the experience replay (ER) module provides random access to past experiences. As a result, these modules or components with each other boost the performance of active self-localization system.

A. NBV Planner

We use deep Q-learning network (DQN) as the basis for our NBV planner. In our view, the model-free property of Q-learning is desirable for the robotic self-localization applications, as it does not include model parameters to be learned and it can intelligently avoid the possibility of learning a wrong model. However, classical Q-learning fails for large-scale problems due to “curse of dimensionality”. The recent paradigm of DQN addresses this issue by approximating the value-action function with a deep neural network. Our approach extends this technique in two ways. First, a part of the deep neural network is replaced with a multi-scale multi-encoder DCN block, derived from the state-of-the-art HED network [8], which is very different and significantly more complex than existing deep neural network employed by typical DQN approaches. Second, the landmark detector is pretrained on Big data before being introduced as a component of the NBV planner.

B. Pole-like Landmark Detection (PLD)

Our PLD network architecture is inspired by the recent paradigm in the field of holistic edge detection (HED) [8].
In particular, we are based on the multi-scale multi-encoder HED network that consists of multiple encoder blocks that act as multi-scale encoder blocks. These main blocks consist of 3x3 convolutional sub-blocks that are densely interconnected by the output of the previous main block, and the outputs of each sub-block are connected between them via a 1x1 convolutional block. The pseudo code of the PLD network $y = f(x)$ is as follows:

$$
y_1 = \text{DoubleConv}(x); \quad s_1 = \text{SingleConv}(x);
y_2 = \text{DoubleConv}(y_1); \quad d_2 = \text{MaxPool}(y_2); \quad x_2 = d_2 + s_1; \quad s_2 = \text{SingleConv}(x_2);
p_3 = \text{SingleConv}(d_2); \quad y_3 = \text{DenseBlock}(x_3, p_3); \quad d_3 = \text{MaxPool}(y_3); \quad x_3 = d_3 + s_2; \quad s_3 = \text{SingleConv}(x_3);
p_4 = p_3^2; \quad y_4 = \text{DenseBlock}(x_4, p_4); \quad d_4 = \text{MaxPool}(y_4); \quad x_4 = d_4 + s_3; \quad s_4 = \text{SingleConv}(x_4);
p_5 = \text{SingleConv}(p_5^2); \quad p_5 = \text{SingleConv}(p_5^2 + d_4); \quad y_5 = \text{DenseBlock}(x_5, p_5);
p_6 = \text{SingleConv}(y_5); \quad y_6 = \text{DenseBlock}(x_6, p_6);
y_7 = \text{Concat}(x \times 1, y_1 \times 1, y_2 \times 2, y_3 \times 4, y_4 \times 8, y_5 \times 16, y_6 \times 16);
y_7 = \text{SingleConv}(y_7); \quad y_7 = \text{Aggregate}(x_7);
y_8 = \text{Activate}(y_7); \quad y_8 = \text{VectorQuantize}(y);
$$

The operations ‘×’ and ‘+’ are the upsampling and addition. DenseBlock, DoubleConv and SingleConv are the dense block, double and single convolutional blocks. MaxPool, Concat are respectively, the max pooling, and concatenate operations. Our implementation basically follows the state-of-the-art HED framework in [8]. However, the HED framework is modified to deal with our DQN task. That is, the 2D edge feature map output by the HED part is spatially aggregated to produce a horizontal 1D image that represents the likelihood of pole-like landmarks (Aggregate). Then, the spatially-aggregated 1D image is further input to the SLA block that consists of a pre-trained activation network (Activate) followed by a vector quantization blocks (VectorQuantize) to produce an extremely compact 4-dim landmark feature map. The aggregation network summarizes the likelihood of pole-like landmark in each different horizontal range in the input image, respectively $[0, W/4 - 1], [W/4, W/2 - 1], [W/2, 3W/4 - 1], [3W/4, W]$, where $W$ is the original image width. Then, the 4-dim vector is passed to the activation network. The activation network is trained only once, in a specific past domain. This 4-dim vector is input to the value-action function block, which is described above. While the locations of pole endpoints in the single train domain are manually annotated in the current study, unsupervised annotation by introducing techniques like pole-based SLAM [6] would be an interesting direction of future research.

### C. Implementation Details

We adopt the spatial bag-of-words (BoW) image model for our PSL module. A BoW model represents every query/mapped image with a collection of vector quantized local visual features, called visual words [11], which are then efficiently indexed/retrieved using an inverted file system. The spatial BoW (SBoW) is an extension of the BoW image model to include spatial information of visual words [12]. We observe that the SBoW is applicable to our case by using the horizontal location of pole-like landmark $(x_o, y_o)$ as the domain-invariant reference for spatial information. More specifically, we compute the spatial information of a given visual feature’s location $(x, y)$ as $(x', y') = (x - x_o, y)$ (Fig. 3).

A bottleneck of the SBoW is the computation cost to simulate the SPL tasks. That is, the cost for querying the SPL image database for each visual image in each query, is in the order of $O(N_{images}N_{words})$ where $N_{images}$ is the number of visual images per experience and $N_{words}$ is the number of visual words per image. To reduce the cost, it is essential to represent the visual experience in a time/spatial efficient and random accessible manner. To address this, we summarize all the possible PSL tasks in a lookup table, which is then used to simulate the experience replay in an efficient manner. Given a pairing of query and map image sets, the lookup table is constructed in the following procedure. First, the SBoW-based information retrieval system is queried for each query image, and top-$K$ retrieval results are obtained. Then, the similarity between the query image and each of the top-$K$ similar map images is computed. Then, the similarity value is compactly represented in a short $B$-bit distance value. The parameters $K$ and $B$ are empirically set $K = 1000$ and $B = 8$ considering the accuracy-compactness tradeoff.

The deep Q-learning network is trained in the experience replay procedure. An experience is defined as a history of planned actions, acquired live images, and states. The NBV action $a$ for the current state $s$ is selected with the probability in proportional to the function $\exp(Q_{a,s})$. Our scheme could be replaced with more advanced experience replay frameworks, such as prioritized experience replay [13] or dueling network [14], which would be a future direction of our research.
A navigation task is terminated if the score distribution becomes a sufficiently narrow distribution. More formally, it is judged if the score of the highest scored location exceeds that of the second scored location with a large margin (0.1).

IV. EXPERIMENTS

We evaluated the effectiveness of the proposed algorithm via active cross-domain self-localization in different domains. We used the publicly available NCLT dataset [15]. The NCLT dataset is a large-scale, long-term autonomy dataset for robotics research collected at the University of Michigan’s North Campus by a Segway vehicle robotic platform. The data we used in the research includes view image sequences along vehicle’s trajectories acquired by the front facing camera of the Ladybug3 as well as the ground-truth GPS viewpoint information. It involves both indoor and outdoor objects such as cars, pedestrians, construction machines, posters, and furniture, during seamless indoor and outdoor navigations of the Segway robot. In our experiments, three different pairings of training and test datasets are used: (2012/1/22, 2012/3/31), (2012/3/31, 2012/8/4), (2012/8/4, 2012/11/17). The four datasets “2012/1/22”, “2012/3/31”, “2012/8/4”, and “2012/11/17” consist of 26208, 26364, 24138, and 26923 images. Images are resized to 320×240.

Figures 1 and 4 show examples of pole-like landmark detection. As shown, the proposed detector successfully detected pole-like landmarks, such as poles, as well as vertical edges of building, walls, and doors. On the other hand, it can intelligently avoided false positive detection of non-structural non-dominant edges, such as tiles on the roads and leaves on the trees.

Figure 4 shows examples of views before and after planned NBV actions. Intuitively convincing behaviour of the robot was observed. When a pole-like landmark is near from the robot viewpoint, the robot tends to plan to move a short distance so as to avoid lose track of the already observed landmarks. Otherwise, the robot tends to plan to move a long distance so as to detect unseen landmarks or approach to already seen landmarks. Such behaviors are intuitively appropriate and effective to seek and track landmarks when one got lost. It is noteworthy that our approach enables to learn such appropriate step sizes from the available visual experience.

Figure 5 shows cost vs. accuracy results for quantitative evaluation. The cost is measured in terms of the number of iterations to reach the termination condition of the active self-localization task, i.e., the confidence score exceeds the preset threshold, which is a function of the number of positive detections of pole-like landmark views. The accuracy is measured in terms of the rank assigned to the ground-truth robot pose when the active self-localization task is terminated.

Our proposed method (“Learned”) is compared against six different methods: “Heuristics”, “Constant (w/ view)”, “Constant (w/o view)”, “Constant (all)”, and “Oracle”. “Heuristics” is a manually designed strategy that selects either of short or long distance move, based on a pre-designed heuristics. Intuitively, long distance move is useful to search for out-of-view landmark objects, while short distance move is useful to approach to landmark objects in the field of view to obtain a closer view of them. Based on the idea, the heuristics selects long distance move $C_{long} + \Delta d$ if there is no detected landmark in the live image, or short distance move $C_{short} + \Delta d$ otherwise, where $\Delta d$ is an artificial motion noise in range $[-1, 1]$ [m]. $C_{long}$ and $C_{short}$ are two different constant parameters that are learned in the training domain.

To learn the constants $C_{short}$ and $C_{long}$, the training image dataset is split into two disjoint subsets, i.e., images with and without pole-like landmark views, and then $C_{short}$ and $C_{long}$, is optimized to maximize for individual subsets the possibility of positive landmark detection. The next three methods, “Constant (w/ view)”, “Constant (w/o view)”, and “Constant (all)”, determine the robot step size, respectively, as $C_{short} + 1$, $C_{long} + 1$, and $C_{all} + 1$, regardless of whether the live image is pole-like landmark view or not. $C_{all}$ is learned in the training domain, in a similar procedure as in $C_{short}$ and $C_{long}$, but by using all the training images instead of the subsets. Cost versus performance for the four pairings of training and test seasons are shown in Fig. 5. It is clear that the proposed approach significantly outperforms all the approaches considered here. It could be concluded that a non-trivial good policy was learned with a model-free DQN from only domain-invariant landmarks and HED images.

V. CONCLUSIONS

In this paper, a novel framework of cross-domain active self-localization using pole-like landmarks was proposed. Unlike previous approaches to active self-localization, we hypothesize that pole-like landmarks are inherently invariant, stable and ubiquitous cue for visual robot self-localization. Based on the idea, a novel multi-scale multi-encoder landmark detection network is introduced to enable detection of holistic essential landmarks, which are then used as the sole input to an off-policy model-free DQN-based NBV planner. The result is a domain-invariant variant of NBV planner that attains consistent performance over different domains, without requiring the expensive task of training data collection and retraining. The effectiveness of the planning algorithm in terms of self-localization performance and domain-invariance was experimentally verified using publicly available NCLT dataset.

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Fig. 4. NBV planning results. In each figure, the top and bottom panels show the view image before and after the planned movements, respectively.

Fig. 5. Cost vs. performance. Vertical axis (cost): travel distance between the initial and final viewpoints. Horizontal axis (performance): ground-truth ranking of the final estimate.

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