Tune your Place Recognition: Self-Supervised Domain Calibration via Robust SLAM

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Abstract—Visual place recognition techniques based on deep learning, which have imposed themselves as the state-of-the-art in recent years, do not always generalize well to environments that are visually different from the training set. To this end, we propose a completely self-supervised domain calibration procedure based on robust pose graph estimation from Simultaneous Localization and Mapping (SLAM) as the supervision signal without requiring GPS or manual labeling. We first show that the training samples produced by our technique are sufficient to train a visual place recognition system from a pre-trained classification model. Then, we show that our approach can improve the performance of a state-of-the-art technique on a target environment dissimilar from the training set. We believe that this approach will help practitioners to deploy more robust place recognition solutions in real-world applications.

Index Terms—Place Recognition, Self-Supervised Learning, SLAM

I. INTRODUCTION

Visual Place Recognition (VPR) remains one of the core challenging problems to solve for autonomous driving, and long-term robot localization. Recognizing previously visited places is essential for decision-making, to reduce localization drift in Simultaneous Localization and Mapping (SLAM), and to improve robots situational awareness in general [1]. While VPR techniques based on deep learning can achieve very high levels of accuracy on standard datasets [2], domain generalization is still a major concern when the deployment environment is visually and/or structurally different from the training data [3]. The problem of domain discrepancies is especially important for indoors or subterranean deployments since most popular approaches are trained on city streets images [4]–[6].

Generalization and feature transferability, from one domain to another, are common issues in deep learning [7] that are studied by research communities from Domain Adaptation [8] to Transfer Learning [9] with encouraging success. Yet, the most common and effective approach is still to calibrate, or fine-tune, the representation to the testing domain. For example, one can refine the network using additional labeled samples directly from the known testing environment to tailor the representation to the target domain. While an effective approach, the data labelling necessary to obtain new training samples can be prohibitively expensive in practice. Therefore, in this paper, we propose a self-supervised domain calibration approach to tune VPR networks to target domains without manual labelling or ground truth information.

First, we show that our self-supervised approach to gather training samples can be used to train a VPR network from a pre-trained classification model and achieve reasonable performance. Thus, demonstrating the strength of our self-supervised training signal in general. Then, we demonstrate that our approach can improve the performance of existing VPR solutions when applied to an environment visually different from the training domain.

Previous approaches [4], [10] relied on GPS localization to extract training samples from datasets by selecting images with minimal distances between them. However, this approach is not suitable for GPS-denied environments such as indoors, underwater or underground. We propose instead to leverage SLAM to collect training samples from an initial, not calibrated, exploration of parts of the environment.

Using SLAM to improve VPR may seem counter-intuitive since it relies itself on precise VPR matches to get an accurate localization. Even worse, errors in place recognition are known to cause catastrophic localization failures in robot state estimation [11]. However, recent progress in robust SLAM has shown that such erroneous VPR matches can be detected and removed during pose graph optimization (PGO) [12], [13]. PGO enables us to leverage the 3D structure from SLAM to filter the matches of a poorly calibrated VPR system to extract correct matches with high confidence. Those correct and incorrect matches can in turn be used to fine-tune the VPR to improve its performance.

Therefore, we believe that robust SLAM can be used as a self-supervision tool for place recognition without any external sensors or ground truth. After calibration, the VPR network is able to detect more correct matches. Moreover, by producing fewer incorrect matches, it reduces the expensive computational burden of processing and rejecting them.

This approach offers practical benefits for the deployment of VPR systems in real applications. It could be used to collect training samples from any sequential dataset, and could be employed online for lifelong learning/tuning on the target environment. Our contributions can be summarized as follows:

- A self-supervised training method for place recognition that does not require any external sensor (e.g. GPS) or ground truth;
- A novel Vision Transformer-based model trained for place recognition using only samples generated with our method;
Self-Supervised Domain Calibration via Robust SLAM: Using a single calibration sequence through a new environment, our proposed self-supervised technique for visual place recognition verifies putative loop closures using recent progress in robust pose graph optimization, and uses the resulting inliers to fine-tune the place recognition network. The place recognition network, tuned to the new environment domain, then achieves better performance on subsequent sequences in visually similar environments. Our calibration approach does not rely on GPS or any ground truth information, and can thus improve place recognition systems in any environment.

- A calibration procedure for existing VPR techniques to improve their performance on any target environment.

In the rest of this paper, Section II presents some background knowledge and related work, Section III details the proposed approach, Section IV demonstrates the effectiveness of the technique, and Section V offers conclusions and discusses future work.

II. BACKGROUND AND RELATED WORK

A. Visual Place Recognition

The ability to recognize places is crucial for localization, navigation, and augmented reality, among other applications [14]. The most popular approach is to compute and store global descriptors for each image to match, followed by an image retrieval scheme using a database of descriptors. Global descriptors are usually represented as high-dimensionality vectors, with dimensions varying from 512 [15] to 70000 [16], which can be compared with simple distance functions (e.g., Euclidean distance) to obtain a similarity metric between two images. The seminal work of NetVLAD [4] extracts descriptors using a CNN and leverages Vectors of Locally Aggregated Descriptors [17] to get a representation well-suited for image retrieval. The descriptor network is typically trained using tuples of images mined from large datasets. An anchor image is first chosen, then positive and negative samples are selected based on close and far GPS localization respectively. A triplet margin loss pushes the network to output similar representations for positive and anchor samples and dissimilar representations for negative ones. Recent work has extended the concept of global descriptors by extracting locally-global descriptors from patches in the feature space of each image [5]. In another line of work, [6] proposed a Generalized Contrastive loss (GCL) function that relies on image similarity as a continuous measure instead of binary labels (i.e., positive and negative samples).

While those major works are based on CNNs, recent developments in Vision Transformers [18] for image classification hints to new capabilities for VPR. Especially since Vision Transformers have been shown to transfer well to other vision tasks [19]. Recent transformer-based works on object re-identification [20], and VPR [21] support this trend and have achieved state-of-the-art performance.

B. Robust SLAM

In SLAM, place recognition is used to produce loop closure measurements between the current pose (i.e., rotation and translation in space) of a robot and the pose corresponding to the last time it has visited the place. Loop closure measurements are combined with odometry (i.e., egomotion)
measurements in a graph representing the robot/camera trajectory. In other words, the SLAM algorithm builds a pose graph with odometry links between subsequent poses and loop closure links between recognized places. Pose graph optimization is then performed to reduce the localization drift of the robot [22]. When using a global descriptor method, such as NetVLAD, VPR serves as a first filter through potential matches, which is followed by the more expensive task of feature matching and registration to obtain the relative pose measurement corresponding to the loop closure. Due to the occurrence of perceptual aliasing (i.e., when two distinct similar-looking places are confused as the same), some loop closure measurements are incorrect and, if left undetected, they can lead to dramatic localization failures [23]. This phenomenon is particularly important when computing loop closures between multiple robots maps for collaborative localization [24].

To mitigate the negative effect of incorrect loop closure measurements during pose graph optimization, several approaches have been proposed. They vary from adding decision variables to the optimization problem [11], [12], performing dynamic covariance scaling [25], or leveraging clusters in the graph structure [26], [27]. For the purpose of this paper, we chose a recent approach based on Graduated Non-Convexity which as been shown to efficiently achieve superior results [13].

It is important to note that these approaches allow us indirectly to classify loop closure measurements, and by extension also VPR matches, as correct or incorrect. In this paper, we leverage this ability to reject spurious VPR matches from the collected training samples.

C. Domain Calibration

The goal of domain calibration is to improve the performance of a system on a target domain different from the domain it has been trained on. This can be done through fine-tuning the model using samples from the target environment or through more complex domain adaptation approaches to enhance the generalization ability of the model. Various approaches have been proposed for in sequence adaption to cope with a changing environment or weather conditions during a mission [28], [29]. As an example, image translation approaches have been proposed to deal with day vs night lighting variations [30]. Incremental training from samples gathered during the exploration has also been shown to work for changing weather conditions [31]. Interestingly, the exploitation of local feature patterns as been identified as a key to domain adaptation since they are more generic and transferable than global approaches [32]. Alternatively, recent work have proposed to include geometric and semantic information into the VPR latent embedding representation for visual place recognition [33] to better adapt to the target domain. The inclusion of geometric or structural information was also explored for domain adaptation in point cloud based place recognition [34].

An approach very similar to ours [10] uses GPS data to extract training samples from a calibration sequence in order to train a VPR system specific to the target environment. Our approach builds on theirs to allow bootstrapping without GPS or any exterior supervision which enables deployments in any environment such as indoors, subterranean, or underwater.

III. Self-Supervised Extraction of Training Samples

The main challenge addressed by our method is to extract pseudo-ground truth labels for training images. To tune the model to the target domain, we need to gather positive and negative place recognition matches from a single preliminary run through the environment. The classic approach is to use external positioning systems (e.g., GPS) to identify images that where captured in the same location as positive samples and images captured in distant locations as negative samples [3]. [10]. We aim to extend this data mining scheme to any environment, regardless of the availability of ground truth localization. Our process is split in three sequential steps. First, we perform SLAM on an initial run through the target environment with a camera, or robot. In particular, we compute visual odometry, and we gather putative VPR matches from an initial network that was not tuned to the specific environment. Second, we filter the putative matches as positive or negative samples using robust pose graph optimization. Third, we use the resulting samples to fine-tune the VPR network to the target domain. A summary of the method is illustrated in Fig. 1.

A. Finding VPR Matches

To perform VPR on SLAM keyframes (i.e., images with sufficient displacement between each other), we first need to process them through a pre-trained network to obtain global image descriptors. Such global images descriptors can be complex structures such as Vector of Locally Aggregated Descriptors [17], used in NetVLAD [4], or simply the features extracted from the penultimate layer of a standard classification network [35]. The descriptors are represented as a vector \( f(I_i) \), where \( f \) is the image representation extraction function and \( I_i \) the \( i \) th keyframe.

As keyframes are processed, we store the computed global descriptors in a database. Then, for each keyframe we query the best matches using nearest neighbors search, by sorting the global descriptors based on the Euclidean distance \( d(q, I_i) \) between the query descriptor \( f(q) \) and the other images descriptors \( f(I_i) \). This results in a sorted list of the best putative VPR matches for each keyframe in the run through the environment. To avoid trivial matches in the same location, we do not consider matches within the 10 previous or subsequent keyframes of the query.

B. Filtering Correct Matches

To filter the VPR matches, we first compute the relative pose between the pairs of images and integrate this information, as loop closures, in the SLAM pose graph. Thus, for each keyframe, we compute the relative pose between itself and the first image in its associated list (the best match). If we are able to successfully compute a relative pose measurement (i.e., loop closure), we store the two images as a (anchor, positive) training sample. Otherwise, we repeat the process with the next best match in the list. To obtain the negative samples, we
go through the remaining best VPR matches in the sorted list and select up to 10 images for which a loop closure cannot be computed due to a lack of keypoint correspondences. This way, we ensure that we extract the negative samples that appear the most similar to the anchor, yet that are not sufficiently similar to compute a loop closure. In other words, we select the most valuable negative samples for training, since they represent invalid VPR matches made by the uncalibrated network. This results in training tuples (1 anchor, 1 positive, 10 negatives) for each keyframe in the sequence.

Given the possible occurrence of perceptual aliasing, the computability of a relative pose measurement between the current anchor and positive frames, is not enough to guarantee that it is a correct place recognition match (see Fig. 2). Using an incorrect sample could contaminate the tuning set and lead the VPR system to even more errors. To avoid this issue, we add the computed relative pose measurements to the SLAM pose graph as a loop closure and perform robust estimation using the Graduated Non-Convexity method \([13]\).

From the resulting optimized pose graph, we can compute the error associated with every measurement and classify the VPR matches as inliers (correct) or outliers (incorrect). We then remove the training tuples corresponding to outliers from the tuning set. Thus, cleansing the tuning set from VPR matches that are in contradiction with the geometric structure of the pose graph.

![Fig. 2: Illustration of the resulting KITTI100 pose graphs with and without an incorrect loop closure.](image)

(a) With 1 incorrect loop closure  (b) Without incorrect loop closure

C. Domain Calibration

The domain calibration of our VPR network is done through fine-tuning using the filtered training tuples in the tuning set. In other words, starting from the pre-trained network, we performed additional training iterations using the extracted data. We applied the triplet margin loss \(L\) for the training tuple \((q, p^n, (n^n_i))\):

\[
L = \sum_i \max(d(q, p^n) + m - d(q, n^n_i), 0)
\]

where \(q\) is the global descriptor of the query image, \(p^n\) is the global descriptor of the positive image associated with the query, and \(n^n_i\) are the corresponding negative samples descriptors. The global descriptors are 1-D vectors resulting from a forward pass through the VPR network and the distance function \(d\) is the Euclidean distance between the vectors. This strategy is analogous to the training method used in NetVLAD \([4]\).

IV. Experiments

Our experiments are divided into two parts. We first demonstrate the quality of the extracted training tuples by using them to train a Vision Transformer network for the task of place recognition. Second, we demonstrate that we can calibrate a state-of-the-art VPR approach for a target domain using our technique.

A. Training a new VPR System

To show the effectiveness of our approach to produce valuable tuning samples from a calibration run through an environment, we trained a new VPR network based only on the samples extracted from a single KITTI-360 \([36]\) sequence. We tested the resulting VPR network on other KITTI \([37]\) and KITTI-360 sequences. All the sequences were collected in the streets of the same mid-size city. We used the KITTI-360-09 sequence for tuning, and the KITTI-\{00, 02\}, KITTI-360-\{00, 02, 06\} sequences for testing. The sequences were selected based on the significant overlaps in their trajectory, which are essential to recognize places.

Our initial model consist of a pretrained Vision Transformer (ViT-B/16 with resolution of 224 \([18]\) for which we removed the classification head. Our choice is motivated by the recent success of Vision Transformers for place recognition \([21]\). We used the feature vector from the penultimate layer (dimension 1x768) as the global place descriptor.

The ViT network was tuned for place recognition using a triplet margin loss with a margin of 0.25 for 10 epochs, which was enough to achieve convergence. We used gradient clipping at global norm 1, a learning rate of 0.001, and cosine learning rate decay as prescribed by \([18]\) for fine-tuning. The relative poses, loop closures, are estimated with stereo pairs, and the `solvePnpRansac` function from OpenCV \([38]\) with a minimum of 6 keypoint correspondences. SLAM visual odometry and pose graph are computed and managed using RTAB-Map \([39]\). Our technique successfully extracted 297 training tuples from the tuning sequence, each comprised of one anchor, one positive, and 10 negative samples.

To validate the training procedure, we computed the similarity score, based on the \(L_2\) distance between global descriptors, of all pairs of images in KITTI-00 sequence. In Fig. 3 we compared the resulting similarity matrix with the one before tuning and the one obtained with NetVLAD. NetVLAD, which is pre-trained on city streets images, is known to achieve high accuracy on the KITTI sequences \([40]\). We can see that our approach converges to a similar result as NetVLAD, especially in the zones where multiple places are revisited and recognized (i.e., high similarity) near the bottom left and right corners (darker blue). The contrast with negative matches is also accentuated.
Fig. 3: Self-Supervised learning of a visual-similarity metric. An illustration of the similarity matrix before (Initial) and after (Tuned) training compared with the similarity obtained from NetVLAD on the KITTI-00 sequence. As expected, the similarity between positive pairs has increased (blue), and it has decreased between negative pairs (white).

KITTI sequences provided in [26], we computed the precision and recall of our VPR system resulting matches before and after tuning. The curves represent the performance for varying detection threshold values for loop closure detection. A loop closure is considered as detected if the distance between the two images global descriptors is inferior to the threshold, there exists sufficient keypoints matches to compute a relative pose measurement, and it passes the test of robust pose graph optimization. We can see a clear improvement after tuning both in precision and recall. It is important to note here that we do not claim to achieve state-of-the-art performance with our new VPR network on the very well-studied KITTI sequences. Rather, we aim to demonstrate the quality and efficiency of the gathered training samples from a single run through the environment without requiring manual labelling or GPS bootstrapping.

B. Calibration of an Existing VPR system

In this set of experiments, we demonstrate that we can improve the performance of a pre-trained state-of-the-art VPR network (NetVLAD) by tuning it to a different target domain. We performed four runs through an indoor office environment (see images in Fig. 1) using an Intel RealSense D455 camera, with multiple overlaps to ensure place recognition. The first run served to extract 166 training tuples, and the three others have been used for testing. We used a margin of 0.25, for 30 epochs with a learning rate of 0.0001 as in the original NetVLAD paper [4].

As shown in Fig. 5, we computed the similarity score for each image pairs in the training sequence before (i.e., initial version of NetVLAD) and after tuning. We can observe a significant improvement in contrast between positive and negative matches hinting to a better distinction between them during testing.

We corroborate this result in Fig. 6 which shows histograms of the $L_2$ distance between all pairs of images. The positive pairs are noted in green and the negative ones in red. Confirming the previous result, the separation between the positive and negative pairs is greater after tuning. It shows that our calibration technique is able to fine-tune the VPR network and distort the feature embedding to increase the distance between
TABLE I: Average percentage of correct matches obtained by NetVLAD before and after tuning. We can see that the domain calibration increased the percentage of correct matches and thus the number of loop closures.

| Indoor Sequence 1 | Indoor Sequence 2 | Indoor Sequence 3 |
|------------------|------------------|------------------|
| Initial NetVLAD  | 65.4%            | 61.7%            | 75.8% |
| Tuned NetVLAD    | 72.0%            | 71.1%            | 82.6% |

Fig. 5: Self-Supervised domain calibration of a visual-similarity metric. An illustration of the similarity matrix before (Initial NetVLAD) and after training (Tuned NetVLAD) compared. As expected, the similarity between positive pairs has increased (blue), and it has decreased between negative pairs (white).

Fig. 6: Separation distance calibration. Histograms of the $L_2$ distance between the positive pairs (green) and negative pairs (red). As expected, the separation increased between the positive pairs and negative pairs after tuning, making it easier to set a VPR threshold.

V. CONCLUSIONS

In this paper, we present a self-supervised training method for place recognition which does not require GPS or ground truth labels for bootstrapping. We demonstrate the efficiency of the method by training a visual place recognition network, based on vision transformer, using only the training samples extracted by our method. We also show that our technique can improve the accuracy of an existing deep learning based place recognition by calibrating it to the target environment.

We consider that our approach has practical benefits for the real-world deployment of place recognition systems. It could be used in an online fashion to perform lifelong learning/tuning on the target environment. Our approach has also the potential for data mining of labeled place recognition training samples on any sequential dataset, which could help increased the overall accuracy of VPR networks. In addition, while we applied our technique to visual sensors, the same approach could be used for other type of sensors used for place recognition (e.g. lidars).

Finally, we believe that leveraging the recent progress in SLAM and robust estimation to improve the performance of deep learning based techniques is a promising avenue that could lead to a tighter integration between the two fields of research.

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