On the Potential of Visual Place Recognition for Visual SLAM

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***Abstract*—This paper outlines the potential of visual place recognition (VPR), used for loop closure detection, to enhance camera-based SLAM. It highlights the gap between state-of-the-art VPR techniques proposed in the literature and those currently implemented in recent Visual SLAM systems. A preliminary experiment further demonstrates the potential benefit of integrating modern VPR methods into future SLAM pipelines.**

I. Introduction

Visual simultaneous localization and mapping (V-SLAM) is the key for truly autonomous robotic systems equipped with cameras operating in GNSS-denied or, more broadly, infrastructure-free environments such as (urban) canyons, caves, mines, extraterrestrial worlds, or disaster zones. V-SLAM is an active research field with numerous proposed methods and systems [1, 2, 3, 4]. An essential component of V-SLAM for building globally consistent maps in large-scale, long-term applications is visual place recognition (VPR) for loop closure detection. Like V-SLAM, VPR is an active research area [5, 6, 7, 8, 9]. However, despite the importance of VPR for V-SLAM, both research fields are quite independent, and recent V-SLAM systems rarely incorporate the latest advancements from the VPR literature. As a result, V-SLAM systems potentially miss the opportunity to achieve higher performance during large-scale, long-duration operation.

In this paper, I briefly outline the potential of modern VPR for enhanced V-SLAM. I begin with an overview of the diversity of VPR techniques, followed by a review of several recent V-SLAM systems to highlight the gap between existing and utilized VPR methods. Finally, I present a preliminary experiment demonstrating that V-SLAM performance improves when better-performing VPR methods are used.

II. Diversity of VPR Methods

There is a rich literature on VPR that proposes diverse methods across various categories to enhance performance and robustness. Below, some of the most important categories are presented to convey an impression of this diversity. A more detailed description of the following categories and corresponding techniques can be found in [11] as well as in the surveys [5, 6, 7, 8]. An introduction to the basics of VPR is provided in [9].

The main challenges for VPR during long-term operation are viewpoint changes, challenging conditions (e.g., fog, snow), and changing conditions (e.g., from day to night). To increase robustness against these challenges, a variety of *local and holistic image descriptors* for image comparison have been developed, including CosPlace [12], D2Net [13], DELF [14], DenseVLAD [15], DinoV2SALAD [16], EigenPlaces [17], HDC-DELF [18], HybridNet [19], MixVPR [20], NetVLAD [21], R2D2 [22], and TransVPR [23]. Note that semantic information can also be integrated into descriptors [24, 25], e.g., to enable loop detection even when the viewpoint is in the opposite direction [24]. Alternatively, *image translation* methods have been proposed that convert the images of different conditions before feature extraction into a single reference condition using different learning-based techniques [26, 27, 28]. To improve the performance of any holistic image descriptor for image comparison, *descriptor transformations* based on principal component analysis [27, 29] or standardization [30, 31] have been applied. *Hierarchical VPR* combines holistic and local descriptors by first selecting matching candidates using the typically faster holistic descriptors, followed by a more accurate but slower verification using local descriptors [13, 32, 33]. Literature on the *efficient comparison of descriptors* focuses on selecting only a subset of image pairs for sparse descriptor comparison by leveraging additional knowledge about the dataset [34, 35]. Instead of computing holistic and local descriptors independently, *descriptor aggregation* combines a set of local descriptors from an image into a single holistic descriptor using approaches such as bag of visual words (BoW) [36, 37], vector of locally aggregated descriptors (VLAD) [15, 38], hyperdimensional computing (HDC) [18, 39], or deep

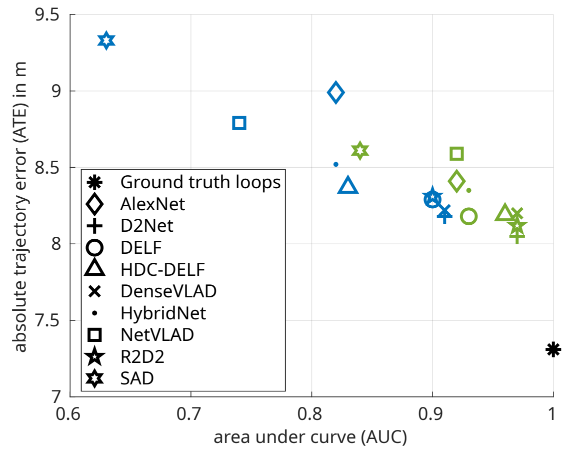

Fig. 1: Relation between performances of V-SLAM (ATE: lower is better) and its VPR component (AUC: higher is better) for all descriptors without and with postprocessing using SeqConv [10]

Visual SLAM / SfM System	Year	VPR System
AirSLAM [51]	2025	PLNet point features [51] + DBoW2 [37] + custom geometric consistency check with LightGlue [52]
Basalt [53]	2019	implicitly using ORB [54] and keypoint matching
DPV-SLAM++ [55]	2024	ORB [54] + DBoW2 [37] and proximity
DROID-SLAM [56]	2021	exhaustive computation of reprojection error between every frame combination
Gaussian Splatting SLAM [57]	2024	(no loop closure detection)
Kimera [58]	2020	ORB [54] + DBoW2 [37] + geometric verification
MASt3R-SLAM [59]	2024	MASt3R-encoder [60] + ASMK [61]
ORB-SLAM2 [62]	2017	ORB [54] + DBoW2 [37]
ORB-SLAM3 [63]	2021	ORB [54] + DBoW2 [37] with custom geometric and temporal consistency check
SuperVINS [64]	2025	SuperPoint [65] + DBoW3 [66]
VINS-Mono [67]	2018	Shi-Tomasi Corner Detector [68] + BRIEF [69] + DBoW2 [37]
COLMAP [70]	2016	RootSIFT [71] + scalable BoW [72]
GLOMAP [73]	2024	RootSIFT [71] + scalable BoW [72]
MASt3R-SfM [74]	2024	MASt3R-encoder [60] + ASMK [61]

TABLE I: Overview of V-SLAM (top) and SfM (bottom) systems with their publication year and used VPR system

learning [32]. *Multi-process fusion* can be used to combine the strengths of multiple descriptors (or potentially other VPR techniques) [18, 40, 41, 42]: For example, some descriptors may perform better in urban environments, while others may be more effective in natural environments [43] or in specific geographic regions such as Western cities [44]. For an even better recognition of known places, especially if the condition slightly changes between each loop, *place-specific descriptors or classifiers* can be used, e.g., based on experiences [45] or support vector machines [46]. Beyond image descriptors, the VPR performance can often be significantly improved using the well-studied *sequence-based methods* [10, 34, 47, 48, 49, 50], which aim to ensure temporal consistency when images are captured along a trajectory.

III. VPR Methods in V-SLAM Systems

Table I reviews several recent V-SLAM systems, along with related structure-from-motion (SfM) systems, including their publication year and the VPR system employed for loop closure detection or correspondence search, respectively. For an overview of six recent LiDAR-centric SLAM systems developed for operation in challenging environments during the SubT Challenge [75], please refer to [76].

Despite the diversity of VPR techniques, many state-of-the-art V-SLAM systems still rely on a limited set of older methods for loop closure detection. For instance, most systems in Table I use hand-crafted local descriptors such as ORB, RootSIFT, or Shi-Tomasi combined with BRIEF, even though the performance of their feature detectors is known to degrade under challenging or changing environmental conditions [15, 77, 78, 79]. Instead, descriptors from the VPR literature designed to handle severe viewpoint or environmental condition changes could be leveraged. However, some systems, such as AirSLAM, MASt3R-SLAM and SuperVINS, do employ deep-learned descriptors that are more robust to significant viewpoint and illumination changes. For computational efficiency, most V-SLAM systems actually adopt a hierarchical approach that first selects matching candidates using a holistic descriptor and then performs geometric verification. Typically, these holistic descriptors are constructed by aggregating local descriptors using methods such as DBoW2 from 2012 or ASMK from 2013. For a temporal consistency check, some of the V-SLAM systems use DBoW's integrated sequence method, which compares three consecutive (key)frames of a loop, although more sophisticated sequence-based methods exist in the VPR literature.

IV. Experimental Evaluation

The following preliminary experiment evaluates the potential of integrating modern VPR methods into a V-SLAM pipeline.

1) Setup: A lightweight pose-graph SLAM is implemented that combines odometry and loop closure detections using a factor graph [80] with Gaussian max mixture model [81] for robust optimization. For pairwise image comparison, one of six holistic or three local image descriptors is used. The resulting pairwise image similarities are optionally post-processed using one sequence-based method as a representative of the broad field of VPR methods beyond descriptors. For evaluation, five traversals through suburban streets from the St Lucia dataset [82] are used. Synthetic odometry data is extracted from GPS with 10% noise. All experiments are repeated 20 times.

2) Result: The results in Fig. 1 reveal a strong correlation between SLAM performance and VPR performance. This suggests that integrating more advanced VPR methods into future SLAM pipelines could further improve the overall SLAM performance. However, the result using ground truth loop closures also highlights the limit of VPR's impact, as SLAM accuracy also depends on (visual) odometry [83], the optimization backend, and the application and trajectory. For instance, V-SLAM on datasets with few, long loops is potentially more affected by missed loops than on datasets with frequent loops.

V. Conclusion

In this paper, I briefly outlined the potential of VPR for V-SLAM. The current gap between VPR techniques in the literature and those currently implemented in V-SLAM systems demonstrates that more sophisticated VPR methods could be integrated into loop closure detection. This could enable future V-SLAM systems to be more robust to viewpoint changes, challenging conditions and severe condition changes, which is particularly important during long-term applications in large-scale environments. A preliminary experiment demonstrated the correlation between VPR performance and V-SLAM performance, suggesting a benefit of using more advanced VPR techniques.

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