Early Bird: Loop Closures from Opposing Viewpoints for Perceptually-Aliased Indoor Environments

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Abstract—
Significant advances have been made recently in Visual Place Recognition (VPR), feature correspondence and localization due to proliferation of deep-learning-based methods. However, existing approaches tend to address, partially or fully, only one of two key challenges: viewpoint change and perceptual aliasing. In this paper, we present novel research that simultaneously addresses both challenges by combining deep-learned features with geometric transformations based on reasonable domain assumptions about navigation on a ground-plane, whilst also removing the requirement for specialized hardware setup (e.g. lighting, downwards facing cameras). In particular, our integration of VPR with SLAM by leveraging the robustness of deep-learned features and our homography-based extreme viewpoint invariance significantly boosts the performance of VPR, feature correspondence and pose graph submodules of the SLAM pipeline. For the first time, we demonstrate a localization system capable of state-of-the-art performance despite perceptual aliasing and extreme 180-degree-rotated viewpoint change in a range of real-world and simulated experiments. Our system is able to achieve early loop closures that prevent significant drifts in SLAM trajectories. We also compare extensively several deep architectures for VPR and descriptor matching. We also show that superior place recognition and descriptor matching across opposite views results in a similar performance gain in back-end pose graph optimization.

I. INTRODUCTION

Visual Place Recognition (VPR) and local feature matching are an integral part of a visual SLAM system for correcting the drift in robot’s trajectory via loop closures. However, multiple complicating factors make this process challenging such as variations in lighting and viewpoint along with the need to deal with dynamic objects. The problem, while challenging in outdoor scenarios, has interesting peculiarities in more structured indoor environments.

Typically, indoor structures (e.g. walls, ceilings) tend to be feature-deficient. Indoor scenes often exhibit strong self-similarity, leading to high perceptual aliasing. Due to these factors, VPR becomes further challenging when a place is revisited from a very different viewpoint and in particular, an opposing viewpoint (180\textdegree viewpoint shift). The latter is a situation commonly encountered when tackling VPR for indoor-based scenarios in warehouses, office buildings and their corridors.

Due to the simultaneous effect of high perceptual aliasing and extreme viewpoint shift, existing state-of-the-art place representation methods tend to perform well. In particular, deep learning-enabled viewpoint-invariant global image representations \cite{1, 9} are unable to deal with perceptual aliasing due to repetitive indoor structures. On the other hand, viewpoint-presumed image representations \cite{4, 9} that maintain spatial layout of the image fail catastrophically due to 180\textdegree viewpoint shift, as also demonstrated in \cite{12}. Therefore, a robust place representation leveraging discriminative regions of an image is much needed to deal with this problem.

Floor texture is a rather under-utilized information source in vision-based applications \cite{6}. While seemingly aliased, in practice, floor patterns contain discriminative features. Blemishes, scratches on the floor surface and natural variations in stone, wood surfaces yield features which can be detected easily across conditional variations \cite{40}. In turn, these enable reliable localization \cite{18, 30}. However, most of the existing solutions based on floor patches require specialised hardware (e.g. downward-facing cameras \cite{30, 28}, additional light sources \cite{18}).

In this paper, we propose an indoor VPR approach which addresses the concerns highlighted previously. We successfully leverage geometrically aligned floor features to provide high fidelity correspondences using state-of-the-art deep feature detector and descriptors. These feature correspondences enable robust pose estimation between opposite views of the same scene having been detected to belong to the same place by the VPR module. The computed pose is exploited by the downstream pose graph optimizer that provides for successful loop detection and closures under extreme viewpoint changes. Thus we provide for a comprehensive pipeline that enables both loop detection and closure under the duress of such viewpoint changes. Specifically we make the following contributions:

- A novel pipeline that combines projective geometry and deep learning architectures to focus specifically on floor areas and consistently improves the individual components: opposite-view place recognition, deep feature correspondences and pose graph optimization;
- Extensive comparisons showing unequivocally that VPR and feature correspondence modules suffer significantly when invoked on raw images while achieve significant boost in performance when invoked on rotationally-aligned floor areas;
- As a consequence of the above two, the paper unveils Early Bird SLAM that integrates opposite-view loop detection and feature correspondence in a back-end pose graph optimizer, demonstrating substantial decrease in
Absolute Trajectory Error (ATE) as compared to the state-of-the-art SLAM frameworks such as [21] which is unable to detect any loops from opposing viewpoints; and
- A comprehensive evaluation of the whole pipeline using a multitude of deep architectures and a variety of real-world and simulated datasets with differing floor textures, smoothness such as stone, marble, concrete, and wooden that verify the repeatability of the proposed pipeline.

II. RELATED WORK

A. Descriptor based recognition

Visual place recognition is an important component of robotic sensing pipelines that enables mobile robot localization. In particular, in the context of visual SLAM, VPR is typically employed for loop closures to reduce the drift in robot’s trajectory.

Amongst the earlier methods, the most popular were appearance-based place descriptors including Bag of Visual Words (BoVW) [34, 7] and Vector of Locally Aggregated Descriptors (VLAD) [17] based methods where a visual vocabulary is constructed using local point-based features like SURF [3] and SIFT [24]. These global image descriptors have been demonstrated to work quite well for VPR as demonstrated in FAB-MAP [8] and ORB-SLAM [29].

Due to lack of appearance-robustness of the underlying local features, whole-image descriptors have also been proposed, for example, Gist [31] and HoG [9]. These whole-image descriptors presume the scene viewpoint to remain similar across subsequent visits of the environment, enabling VPR under extreme appearance variations as demonstrated in SeqSLAM [26]. However, the aforementioned techniques rely on hand-crafted features and have been successfully replaced with modern representation techniques based on deep learning as described in subsequent section.

B. Robustifying VPR

CNNs have a certain degree of appearance and viewpoint robustness built in due to the spaced convolutions and the pooling layers, and have been shown to be good at visual place recognition [4, 35]. They allow for end-to-end training where one can in addition to using off-the-shelf networks [1], train the later layers to obtain task/dataset specific results [33].

In [5], pyramid pooling was shown to improve viewpoint robustness. However, this method required specifying salient regions of the feature map. Subsequently, as an improvement to this manual specification, methods intelligently extracting these keypoint locations within these feature maps have been proposed [38]. [22] proposed cross-convolutional pooling, utilizing the spatial position of activations of later layers.

Another interesting avenue of research that was proposed recently involved view-synthesis. In [36] a query RGBD-image was densely sampled to obtain a 6D-pose (camera location relative to a reference frame) of the scene using a RANSAC-like procedure. Pose verification was then done by rendering a transformed virtual view of the query image. However, most of the research to date deals with appearance robustness and viewpoint variations only in isolation; the existing methods tend to fail under a simultaneous effect of high perceptual aliasing and significant viewpoint variations.

C. Opposing Viewpoints

Most of the existing literature that addresses viewpoint-invariance for VPR implicitly assumes a large amount of overlap in the Field of View (FoV). The subset of the literature dealing with VPR from opposing viewpoints is quite sparse even though this is a commonly encountered situation, ex. a warehouse robot moving up and down a corridor. To deal with minimally-overlapping viewpoints, highly-engineered solutions based on specific sensor modalities have been proposed, for example, those based on LiDAR [39] and panoramic vision [2]. However, enabling viewpoint-invariance for limited field-of-view, forward-facing cameras
can be a potentially more versatile solution, particularly for resource-constrained deployments.

Recently, there have been some attempts to address the problem of simultaneous robustness to appearance and viewpoint variations. LoST [13] is one of the few works that deals with opposing viewpoint recognition using a limited-FoV camera. They use dense semantic information to represent places and extract keypoints from within the CNN to enable high-performance VPR. This was improved upon in [14] using a topo-metric representation of places. In particular, they employed monocular depth to accrue keypoints from a reference sequence of images in order to maximize its visual overlap with the query image from opposing viewpoint. In the vein of utilizing higher-order semantics, X-view [15] uses dense semantic segmentation and graph-based random walks to perform VPR across aerial and ground view. [19] uses satellite imagery to perform localization by matching aerial and ground view data by learning location-discriminative embedding.

However, the above methods have primarily been developed for outdoor environments and are not adaptable straight away for indoor settings where the challenges are quite different. For example, the crop and flip strategy proposed in [12] for dealing with opposite-viewpoint VPR may not be used in corridors or indoor aisles that appear similar on both the sides (left and right) which is not usually the case for road-based imagery. Similarly, the choice of semantic classes [13] for outdoor environments is not directly transferable to indoor scenes.

D. Saliency of floor features

In [40], features are extracted from different floor surfaces (granite tiles etc.) to perform global localization. The imperfections and natural variations in the tiles from high-resolution imagery provide enough features that salient and persistent key-points can be extracted. In [25], a warehouse automation system was introduced to track the robot using cracks and scratches observed on the ground surfaces. They assumed a known initial location and surface textures are leveraged only for bipartite matching between query and reference images. With a focus on surface-based localization, researchers have also explored robust methods for match verification [28] and coverage selection [27] using ground-based imagery. [18] proposed to use floor patches to perform local region matching in order to develop an infrastructure-free localization system. In [30], authors developed a visual odometry system based on floor patches.

Going a step further from the use of floor-based patterns, it has also been demonstrated that seemingly-random patterns can also allow for unique identification, for example, minor variations in a piece of paper could be used to compute a descriptor that uniquely identified it [6]. Furthermore, use of ceiling [37] has also been explored in the context of surface-based localization.

In contrast to the aforementioned approaches, our proposed pipeline does not require specialised hardware alternatives, for example, downward-facing cameras [30, 27] or additional light sources [18, 32]. Furthermore, we exploit floor features for feature matching across forward and backward traverses which has not been tackled explicitly by any of the existing floor-based VPR systems.

E. Keypoint Correspondences Matching

Calculating the pixel level correspondences between images is a well-studied problem in computer vision for tasks like tracking and localization. Classical approaches like SIFT [23] and SURF [3] tackle this problem in a two-way approach by first detecting the keypoints and then describing a local region around the keypoint. Recent learning-based approaches like SuperPoint [10] and D2Net [11] combine detection and description by simultaneously optimizing for both the tasks. However, none of the approaches work well when deployed in perceptually-aliased and low-textured indoor settings, particularly when viewing a scene from an opposite direction. In the context of a robotics application, we show that the existing deep-learned feature correspondence methods can lead to better matching by using certain regions of the image like floor and exploiting geometric priors between images in the forward and reverse trajectory.

III. METHODOLOGY

Our proposed hierarchical pipeline consists of the following three stages: indoor visual place recognition for opposite viewpoints, feature correspondence extraction and pose graph optimization.

A. Indoor visual place recognition for opposite viewpoints

While the method makes use of deep-learned features, it requires no environment-specific training of the underlying feature extractor.

Our approach to indoor VPR makes use of the fact that floor patches contain useful features in the form of cracks (wear and tear), designs (tiles), dirt/stains as also established in prior literature [18, 30, 40, 27] but we demonstrate its utility without requiring specialised hardware. The floor-based features act as a unique signature for specific places within an indoor region, identifiable even from opposing viewpoints. We leverage this to demonstrate applications of our proposed method to visual SLAM with early loop closures that significantly reduce the time to drift-correction in the robot’s trajectory.

To extract the floor-region of the images taken, we fit a planar homography $H$ to image points via a RANSAC + 4 point algorithm [16].

In this case, we use a fixed homography matrix across all the datasets. In the original image, we pick four points along the floor region which are then transformed into a floor image. Since there is no lateral shift between the forward and backward trajectories, the same homography matrix ensures enough overlap between the floor transformed images from the backward and forward trajectories.

Let $H$ be the homography matrix, $x$ be a homogenized coordinate of an input image then the transformed image
co-ordinate, $\hat{x}$ is obtained via eq. (1).

$$\hat{x} = H(x)$$

(1)

Figure 2 shows example images from our benchmark datasets with both the raw images and their corresponding floor patches so obtained.

In our pipeline, we pass the floor patch images obtained into a deep feature extractor and the output descriptor forms our place representation.

$$d_i^q = f(\hat{x}_i^q)$$

(2)

where $f()$ corresponds to the process of obtaining features from a deep feature extractor and $d_i^q$ is the resultant descriptor obtained for image $i$. Cosine distance-based descriptor matching is done to obtain matches between $Q$ and $D$. We apply the homography operation on the reference and then perform a 180° rotation of the transformed images to improve matching across differing viewpoints of the same place. Although the rotation/flipping operation is not necessary for some of the deep feature extractors as they are inherently viewpoint-invariant, we show that performance can be boosted for such descriptors whereas other viewpoint-presumed deep feature description techniques become only useful post image rotation.

B. Feature correspondence extraction

Both classical feature detectors and descriptors like SURF [3] and deep learning based methods like SuperPoint [10] and D2Net [11] fail to find correspondences from opposite viewpoints due to limited visual overlap and high perceptual aliasing in indoor settings as depicted in Figure 4 (1a and 2a). SuperPoint is trained by generating homographies of a single image which does not take into account the opposite viewpoint images. D2Net is trained on outdoor SfM dataset by utilizing fifty percent minimum overlap between point clouds, which is not the case in opposite viewpoint scenes.

By utilizing the previously proposed concept of applying geometric transformations on image to extract textured floor regions enables us to generate very precise pixel level correspondences Figure 4 (1c and 2c). These precise correspondences are also very essential to calculate near ground truth transformation and subsequent loop closure in pose graph SLAM Figure 5 on real dataset and Figure 6 on synthetic dataset.

| Input OP | D1 | D2 | D3 | D4 | D5 | D6 | D7 |
|----------|----|----|----|----|----|----|----|
| Raw None | 24.1 | 22.1 | 24.8 | 19.9 | 9.7 | 28.5 | 22.2 |
| Raw Flip-L-R | 28.8 | 26.8 | 29.1 | 26.6 | 12.5 | 29.2 | 20.6 |
| Homo None | 60.7 | 62.7 | 61.3 | 70.4 | 40.1 | 12.2 | 15.1 |
| Homo $\pi$-Rot | 69.3 | 70.1 | 71.8 | 73.3 | 44.7 | 16.3 | 28.8 |

TABLE I: Quantitative Analysis: First column shows the pre processing operation of the input image. Raw and Homo denote that we use Raw images and homography transformed images as input. Second column shows types of transformation operations (Op) applied on the reference images. $\pi$-Rot and Flip-L-R indicate a 180° rotation and horizontal left-to-right flipping of the reference image respectively. Homo + $\pi$-Rot gives the best results (bold) in most cases and hence is an important and a necessary operation. NetVLAD is used as the deep feature extractor.

Let $x_Q$ be the query image and $x_M$ be the matched image from the opposite trajectory obtained via the VPR pipeline. $\hat{x}_Q$ is the transformed image obtained by applying homography and $\hat{x}_M$ is the transformed image obtained by applying homography and $\pi$-rotation. Figure 3. Local feature extractor $g()$, in our case D2Net is used to obtain correspondences $\hat{q}^{2D}$ and $\hat{m}^{2D}$ on transformed images. Corresponences on the original image $q^{2D}$ and $m^{2D}$ are obtained by inverse $\pi$-rotation and inverse homography.

$$\hat{x}_Q = H(x_Q)$$

(3)

$$\hat{x}_M = R_{\pi}(H(x_M))$$

(4)

$$\hat{q}^{2D}, \hat{m}^{2D} = g(\hat{x}_Q, \hat{x}_M)$$

(5)

$$q^{2D} = H^{-1}(\hat{q}^{2D})$$

(6)

$$m^{2D} = H^{-1}(R_{\pi}^{-1}(\hat{m}^{2D}))$$

(7)

C. Pose graph optimization

The proposed VPR pipeline has direct applicability in loop closure or data association problem in visual SLAM. Formally, we are interested in finding the optimal configuration $X^*$ of robot poses $x_i$ based on odometry constraints $u_i$ and loop closing constraints $c_{q,m}$. Here, odometry constraints $u_i$ are used to build the motion model whereas loop closure constraints $c_{q,m}$ provide information to correct the error accumulated due to sensors’ noise.

Let $S$ be a set of image pairs proposed by VPR such that, $S = \{(q,m)|I_q \in Q, I_m \in R\}$, then optimal poses $X^*$ are given by:
We have used seven real-world indoor datasets in our experiments as shown in Figure 2. Six datasets were collected in various parts of a University campus and one dataset was collected inside a house. The datasets comprise of different types of floor types like marble, wooden, concrete and carpet. The datasets consist of sequences in range of 15 m to 50 m. Each sequence contains anywhere between 500-4000 images. For calculating the homography matrix, we choose the floor patches which are at a closer depth to the camera. Of the seven datasets, five were collected using a OnePlus 6 smartphone and two were collected using GoPro Hero 3+. The OnePlus 6 and the GoPro Hero 3+ recordings were collected at 60 and 24 fps respectively. We have shown the application of VPR pipeline in a SLAM framework, Figure 5, on one of the dataset collected on the university campus with P3DX robot equipped with RealSense D435 and wheel odometry. Additional ablation studies of the effect of early loop closures on the ATE of SLAM pose graph is done on three synthetic datasets, Figure 6 (last column), where floor tiles are chosen from real world images and P3DX noise model have been incorporated in the simulator odometry data.

### B. Evaluation and Comparisons

We evaluate the performance at each stage of our pipeline. The results are categorized as follows: (i) Visual Place Recognition Results (ii) Feature correspondence results and (iii) Loop closure results.

Similar to existing works [14, 1], we use Recall as an evaluation metric for visual place recognition, defined as the ratio of true positives and total number of positives. A match is said to be a true positive if it lies within a localization radius of \( \frac{1}{15} \)th of the total length of the traversal of its ground truth. We compare various deep feature extractors under different input settings.

For the feature correspondence results, performance of different types of input transformations is shown qualitatively and quantitatively in Figure 4 and Table III respectively. A correspondence match is considered to be an inlier if its reprojection error calculated using ground truth transformation is below a threshold. Comparison among classical approach SURF [3] and learning based approaches SuperPoint [10] and D2Net [11] has been shown in Table III.

Comparison between our early loop closures with traditional loop closures like in RTABMAP [21] where robot needs to revisit the place from the same viewpoint have been shown. We have compared Early Bird loop closures with state of the art SLAM method RTABMAP in terms of Absolute Trajectory Error (ATE) on both real world and synthetic datasets.

### V. Results

We show results for each of the components of our pipeline, particularly highlighting the effect of geometric transformations for both VPR and feature correspondences which ultimately contribute in improving the trajectory error for the SLAM back end. First, we show results for VPR with ablations across a multitude of place descriptor and geometric transformation types. Then, we show results for feature correspondence extraction both qualitatively and
quantitatively. Finally, we compare our Early Bird SLAM pipeline with the state-of-the-art SLAM system RTABMAP in terms of Absolute Trajectory Error (ATE) on real and synthetic datasets.

A. Visual Place Recognition

Table I and II show the recall performance for VPR using seven different datasets. While Table I highlights the effect of geometric transformations on a given place descriptors, NetVLAD in this case, Table II compares different descriptor types for the best performing geometric transformation, that is, Homo + \( \pi \)-Rot. It can be observed in Table I that using the raw images (Raw) as input leads to inferior results for most of the datasets even when using the state-of-the-art viewpoint-invariant representation NetVLAD. The best performance is achieved through 180-degree rotation of floor patches (Homo + \( \pi \)-Rot) as compared to when using only the homography transformed input (Homo). We also compute descriptors using horizontally-flipped images (Flip L-R) as used in [12, 13] for dealing with opposing viewpoints in outdoor environments. It can be observed that such a transformation does not lead to consistent performance gains. We attribute this to the repetitive and featureless nature of indoor environments. For D7, a small performance gap is observed between using Raw and geometrically transformed images (Homo + \( \pi \)-Rot); this is due to the reduced aliasing because of availability of unique visual landmarks when using raw images. In D6, raw images (Raw) perform better than floor (Homo + \( \pi \)-Rot) images due to the lack of sufficient visual features on the carpet floor. This limitation could potentially be overcome by using a joint VLAD aggregation of the whole image and the transformed image, and remains a future work.

In Table II we compare the performance of different feature extractors under the best input setting (Homo + \( \pi \)-Rot). NetVLAD performs the best in most cases with ResNet being the second best. While NetVLAD is a viewpoint-invariant representation, ResNet-based feature extraction assumes the viewpoint to be the same after geometric transformations. However, due to lateral offsets in repeat traversals in opposite direction, a viewpoint-invariant representation has more advantages which is reflected in Table II. Nevertheless, due to high perceptual aliasing, geometric transformations are still required before descriptor computation in order to achieve the best performance, as demonstrated in Table I.

We show qualitative results of using the state-of-the-art VPR method NetVLAD on various indoor datasets and compare it with Resnet in the supplementary material section.

B. Feature Correspondence

Estimating precise correspondences are crucial to calculate accurate transformations using ICP like registration methods, which in turn help us to achieve near ground truth pose estimates. Figure 4 (1a and 2a) show that using raw images to calculate feature correspondences cause both SURF and state-of-the-art learning methods SuperPoint and D2Net to fail. The number of correct correspondences increase with the use of geometric transformations focusing on textured floor regions. However, without image rotation, matching still remains poor as shown in Figure 4 (1b and 2b). The best results are obtained when transformed image pair is aligned with each other by 180° rotation as shown in Figure 4 (1c and 2c). Table III quantitatively shows the number of inliers as well as total correspondences, averaged over all the datasets, using different feature extractor methods. It can be observed that after the geometric transformation, D2Net leads to a large number of initial as well as final correspondences. Thus, we used D2Net with homography and \( \pi \)-rotation as the final keypoint extractor approach for calculating transformations in subsequent tasks.

|                | SURF       | Superpoint | D2Net     |
|----------------|------------|------------|-----------|
| Raw            | 4.5 / 6.5  | 0.5 / 6.5  | 0.6 / 28.5|
| Homo           | 8.5 / 9    | 4 / 5.5    | 6.5 / 13  |
| Homo + \( \pi \)-Rot | 11.5 / 11.5 | 10 / 11.5  | 97.5 / 97.5|

Table III: Number of Inliers / Total Correspondences averaged over all datasets

C. Loop Closures in Early Bird SLAM

In practical scenarios in the context of long term autonomy, a robot can typically revisit its operating environment from a variety of different viewpoints. A more common scenario particularly in corridors and aisles is that of an opposite viewpoint which is when our proposed system triggers loop closure. We demonstrate its efficacy by comparing with the state-of-the-art SLAM system RTAB-Map [21]. As shown in the Table IV (Dataset D5), we significantly reduce the Average Trajectory Error (ATE) by detecting “early” loop closures which is qualitatively shown in Figure 5 while RTABMAP fails to do so, due to significant perceptual aliasing. As a consequence, the RTABMAP’s trajectory Figure 5 (top left) shows multiple corridors when actually there is only...
Fig. 5: Rows represent pose graph and registered map. The first column corresponds to RTABMAP trajectory with robot revisiting the location from opposite viewpoints, blue dashed line represents early loop closures on pose graph, second and third column corresponds to optimized map based on VPR constraints and ground truth map respectively.

Fig. 6: Each row represents pose graph optimization done on three gazebo environments corresponding to Table IV. First column corresponds to RTABMAP trajectory with robot revisiting the location from opposite viewpoints. Second and third column corresponds to optimized and ground truth trajectory.

Ablation study has been done on measuring the usefulness of early loop closures with different robot’s trajectory length and different tile patterns. We have performed our experiment in three different simulated environment settings as shown in Figure 6. In all the three cases, we have achieved near ground truth poses, while state of the art SLAM method RTABMAP fails to detect any loop closure while returning to the same place from opposite viewpoints. These results are quantitatively represented in terms of ATE in Table IV, showing that with increase in the length and complexity of the trajectory the effect of early loop closures becomes even more pronounced.

VI. Conclusion and Future Work

This paper proposes a novel pipeline that integrates Visual Place Recognition (VPR) with SLAM front and back ends specifically for loop detection and closure for opposite views using our VPR pipeline. These are much closer to ground truth trajectory and map shown in (last) column of Figure 5.

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Table IV: Average Trajectory Error on a university dataset and three gazebo datasets for RTABMAP loop closures vs Early Bird loop closures

| Datasets | RTABMAP | Early Bird |
|----------|---------|------------|
| D5       | 9.239   | 5.69       |
| S1       | 0.94    | 0.26       |
| S2       | 2.86    | 0.38       |
| S3       | 2.85    | 0.36       |

The future threads include extension to outdoor and warehouse like topologies, use of visual semantics or monocular depth-based ground plane extraction and learning an attention mechanism to deal with the simultaneous effect of viewpoint variations and perceptual aliasing.

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