NERF-SUPERVISED FEATURE POINT DETECTION AND DESCRIPTION

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ABSTRACT

Feature point detection and description is the backbone for various computer vision applications, such as Structure-from-Motion, visual SLAM, and visual place recognition. While learning-based methods have surpassed traditional handcrafted techniques, their training often relies on simplistic homography-based simulations of multi-view perspectives, limiting model generalisability. This paper presents a novel approach leveraging Neural Radiance Fields (NeRFs) to generate a diverse and realistic dataset consisting of indoor and outdoor scenes. Our proposed methodology adapts state-of-the-art feature detectors and descriptors for training on multi-view NeRF-synthesised data, with supervision achieved through perspective projective geometry. Experiments demonstrate that the proposed methodology achieves competitive or superior performance on standard benchmarks for relative pose estimation, point cloud registration, and homography estimation while requiring significantly less training data and time compared to existing approaches.

Keywords Feature detection and description · Neural Radiance Fields · Datasets

1 Introduction

Feature point detection and description under different scene viewpoints is a common starting point for many multi-view problems including Structure-from-Motion [1], visual SLAM [2, 3], or visual place recognition [4, 5]. In the past decade, different learning-based approaches to this problem [6, 7, 8, 9] have replaced handcrafted techniques in many applications [10, 11, 12]. Crucially, most of these models can be fine-tuned in a self-supervised manner on any single-view dataset. This is achieved by applying different homography warpings to the training data, simulating different viewpoints of the same scene with known point-to-point "ground-truth" mappings. While this training scheme is simple and flexible, the generated homography warpings are a crude simplification of multi-view perspectives, which can lead to limited model generalisability.

This paper aims at leveraging image synthesis with neural radiance fields (NeRFs) as a more realistic way of generating multi-view training data for feature detection and description models (see Fig. 1). Since NeRFs require multi-view data to synthesise novel views, we can no longer rely on the single image datasets typically used for training the above-mentioned homography-based methods. Therefore, we create our own dataset consisting of indoor and outdoor image sequences around static scenes and reconstruct all of them with NeRFacto [13]. This enables the generation of arbitrary viewpoints of each scene consistent with a pinhole projective model with known point-to-point mappings via point re-projection. We propose a general methodology to upgrade state-of-the-art homography-based methods to train them on projective views synthesised from NeRF-type algorithms. Our contributions are as follows:

- We create a new multi-view dataset consisting of images from 10 different indoor and outdoor scenes, and a
 total of 10000 NeRF-synthesised views from these scenes with corresponding depth maps, and intrinsic and
 extrinsic parameters.
- We propose two general methodologies (end-to-end and projective adaptation) to train state-of-the-art point detection and description methods using a loss function based on NeRF re-projection error.

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(a) Input Image

(b) Image w/ Homography

(c) Image Diff. Viewpoint

Figure 1: **Visual representation of multi-view data.** Learning-based detectors and descriptors achieve supervision on single-view datasets by simulating different viewpoints through homographic warpings to the input image I (see Fig. 1a) resulting in I' (see Fig. 1b). However, we achieve supervision by directly sampling a NeRF-rendered image from a different viewpoint (see Fig. 1c).

• We re-train adapted versions of SuperPoint [6] and SiLK [14] using our NeRF-synthesised data and compare them against the original baselines trained on the much larger MS-COCO dataset. We outperform the original baselines for relative pose estimation on ScanNet, YFCC100M and MegaDepth datasets [15, 16, 17], with similar performance for pair-wise point cloud registration, while only slightly under-performing on the HPatches homography estimation benchmark.

2 Related Work

Research on multi-view feature detection and description has a large focus on creating representations invariant to geometric transformations (*e. g.* scale, rotation, affinity) and illumination conditions so that the same scene point can be reliably recognised and matched regardless of its viewpoint. Classic methods achieved this by handcrafting feature extractors that incorporate these invariance properties by design. Some of these decade-old methods stood the test of time and are still widely used today [18, 19]. More recently, the success of deep feature extraction enabled neural networks to learn these invariance properties from training data. Large open-source datasets [20, 15, 17] have been extensively employed to train either learning-based interest point detectors and descriptors [6, 21, 14, 22], or detector-free local feature matchers [23, 24, 25].

Some of these methods [6, 14] are trained in a self-supervised manner on uncalibrated RGB single-view datasets such as MS-COCO [20] by simulating multiple views as homography warpings. Other methods [21, 22] are trained with additional supervision using calibrated multi-view RGB-D datasets such as ScanNet [15]. These two classes of methods have pros and cons. The multi-view data generated by self-supervised methods is not representative of all possible viewpoint changes (homographies only model planar scenes or pure rotations). Thus it does not fully generalise to some application scenarios. On the positive side, they can be trained on an arbitrarily large number of transformations, and are also extremely flexible as they can be fine-tuned on any uncalibrated single-view dataset. Fully supervised methods are trained on more realistic multi-view data that covers full projective view changes with occlusions, however, the required training data is significantly more complex to obtain. The variety of scenes and viewpoint changes in the training data are also limited by the practicalities of real data acquisition. To get the best of both worlds, we propose using NeRF reconstructions obtained from RGB image sequences, which are both simple to acquire and enable the synthetic generation of arbitrary projective viewpoints beyond homographies.

Progress on image synthesis with NeRF and its variants [26, 27, 28] has exploded in the past years, with very fast improvements in computational efficiency, image synthesis quality, reconstruction accuracy, and input data requirements. As these techniques enable synthesising arbitrary viewpoints of a reconstructed scene, they can be used for rich data augmentation [29]. Most related to our work, they have been utilised to self-supervise multi-view methods for learning viewpoint invariant object descriptors [30], stereo disparity [31], and optical flow [32]. However, to the best of our knowledge, NeRF self-supervision has been under-explored for point feature detection and description.

3 Methodology

3.1 NeRF Dataset

We build a NeRF dataset for 10 indoor and outdoor scenes, containing 10000 synthetic images with their corresponding intrinsic/extrinsic parameters and depth maps. We note that this dataset is extremely small compared to what is typically used to train state-of-the-art feature detection (30 times smaller than MS-COCO, 250 times smaller than ScanNet). Our goal is to show that leveraging NeRF supervision enables state-of-the-art performance on multiple benchmarks with significantly less training data.

We captured four indoor and one outdoor scenes with an iPhone 10 at 4K resolution, and one indoor and one outdoor scene with a Samsung A52 at 4k resolution. We also utilise two blender-generated indoor scenes with images sourced from [33] and one outdoor scene publicly available through [34] as they are open-source scenes that consist of high-quality RGB images. While different training sets could be constructed using existing publicly available data, we focus on a trade-off between scene diversity and minimal dataset size.

We obtain camera poses for all images using COLMAP [35] and use them to generate synthetic views. We trained a Nerfacto model for each scene, which is part of the NeRFStudio framework [13] and merges improvements from a range of NeRF implementations [36, 34, 37, 38]. For each scene, we rendered 1000 synthetic views and corresponding depth maps with 44° field of view and 640×480 resolution. We use NeRFStudio's interactive real-time viewer to define custom camera trajectories for each scene that ensure diversity in viewpoints while maintaining global scene overlap. Trajectories consist of uniformly sampled smooth trajectories around the scene coupled with small rotations around the camera centre.

3.2 NeRF Point Re-Projection

Similarly to prior self-supervised methods [6, 14] we consider neural networks that, at inference time, detect interest point locations \mathbf{p} and extract their descriptors \mathbf{d} from a single view. Consider two views I, I' synthesised by NeRF with known intrinsic $(\mathcal{K}, \mathcal{K}')$ and extrinsic $(R, R', \mathbf{t}, \mathbf{t}')$ parameters. For any arbitrary point with homogeneous pixel coordinates \mathbf{p} in image I, we know its NeRF reconstructed depth d and can represent it in 3D world coordinates as:

$$\mathbf{P} = [R|\mathbf{t}] \frac{\mathbf{p}_c}{||\mathbf{p}_c||} d, \quad \mathbf{p}_c = \mathcal{K}^{-1} \mathbf{p}.$$
 (1)

Similarly, \mathbf{P} can be re-projected into view I' as:

$$\mathbf{p}' = \mathcal{K}' \frac{\mathbf{P}'}{\mathbf{P}'_z}, \quad \mathbf{P}' = [R'^T | -R'^T \mathbf{t}'] \mathbf{P}. \tag{2}$$

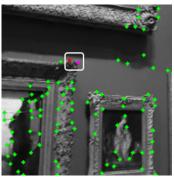
Assuming that reconstructed depths d are accurate, the above equations enable supervising a point detector, by designing a loss function that promotes a set of re-projected points \mathbf{p}' detected in view I to align with points independently detected on view I'. However, many distinctive interest points lie on scene edges at a depth discontinuity. This means that even a small deviation in \mathbf{p} can cause significant variations in d, corresponding to the depths of the background and foreground around the edges. To ensure stable re-projection around edges, we differentiate between foreground and background by focusing only on the foreground around the edges, excluding the background. To achieve this, we compute d within a 5×5 pixel window centred around \mathbf{p} . If the difference between the maximum and minimum depths within this patch does not exceed a predefined threshold ϵ_d , we take d at the interest point position. Otherwise, we use the minimum depth within the window (see example in Fig. 2).

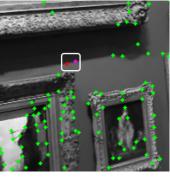
4 Implementations

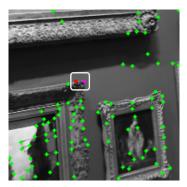
4.1 SiLK-PrP

Self-supervised point detection methods that are trained end-to-end can be easily adapted to utilise NeRF training data. Using SiLK [14] as a baseline, we propose an adapted version that, during training, simply replaces homography warpings with NeRF renderings and point re-projection, while keeping the rest of the training pipeline and loss functions intact.

In the original SiLK approach, image pairs with ground-truth bi-directional correspondences are generated on the fly during training with homography warpings. We rely on our pre-rendered NeRF dataset described in section 3.1, to







(a) Input Image

(b) PrP w/o Depth Window

(c) PrP w/ Depth Window

Figure 2: **Depth window estimation.** The interest points, depicted in red and purple situated at the painting's frame in Fig. 2a, exhibit misprojection onto image $I^{'}$ without the depth window estimation method. However, misprojection errors are effectively mitigated by utilising the depth window estimation method as seen in Fig. 2c.

avoid significant computational overhead caused by on-the-fly image rendering. During training, we randomly sample image pairs I, I' from the same scene, Eqs. 1 and 2 are then utilised during training to generate dense ground-truth point correspondences, discretised at the pixel level.

4.2 SuperPoint-PrP

SuperPoint is a self-supervised method that goes through multiple stages of training. Firstly, an encoder with a detector head is trained in a fully supervised manner to detect corners on a synthetic dataset with simple geometric shapes. The pre-trained detector, called MagicPoint, is used to generate pseudo-ground truth interest points on a real dataset (*e.g.* MS-COCO) using a process called homographic adaptation. This involves generating several homography warped copies of a training image, passing them through the trained detector, unwarping all predictions back to the original training image, and finally aggregating all unwarped predictions to generate the pseudo label. This process can be repeated several times, where after each round of homographic adaptation, the detector head is further trained, updating the pseudo-ground truth labels, while improving the detector head's generalisability. After a final round of homographic adaptation, a descriptor head is added to the model, which is jointly trained with the whole model with an additional descriptor loss term on the real dataset resulting in the SuperPoint model.

With the NeRF training data approach, we use the same architecture as the original SuperPoint model. However, modify the homographic adaptation process as well as the descriptor loss to handle our NeRF training data and Point Re-Projection process.

4.2.1 Projective Adaptation

Similarly to our SiLK-PrP approach, we consider pre-rendered NeRF images as training data. In this case, we exploit the fact that training sequences for each scene are generated along a continuous trajectory.

We randomly sample from a window of 20 consecutive rendered NeRF images $I_{i\rightarrow i+19}$. We take pseudo-ground-truth points for the initial image I_i and randomly sample a set of 14 of the remaining 19 images as the warped versions of I_i . An image from the randomly sampled set is denoted as I_r .

The probability heatmap $\mathbf{H_i}$ for image I_i is then computed. For each image I_r in the randomly selected set, its corresponding probability heatmap $\mathbf{H_r}$ is computed. Interest points $\mathbf{p_r}$ are then extracted from each heatmap, employing non-maximum suppression to filter out feature points that are too close to each other.

Once interest points $\mathbf{p_r}$ are obtained, the PrP process is applied to project the interest points aligning them with the initial frame I_i , to clarify the projected interest points from I_r to I_i can be denoted as $\mathbf{p_i'}$.

Having obtained the projected interest points $\mathbf{p}_{i}^{'}$, we generate a mask denoted as $\mathbf{H}_{i'}$, for each interest point in $\mathbf{p}_{i}^{'}$ coordinates on the binary mask, a 3x3 patch centred around the interest point before projection is extracted from the probability heatmap \mathbf{H}_{r} , the patch is then applied on the binary heatmap $\mathbf{H}_{i'}$. Thus, mask $\mathbf{H}_{i'}$, serves as the probability heatmap of rendered image I_r projected onto the input render frame I_i .

Finally, the input's rendered image probability heatmap $\mathbf{H_i}$ and mask $\mathbf{H_{i'}}$ for each frame, are aggregated together, non-maximum suppression is applied once more on the final aggregated heatmap to obtain pseudo-ground-truth interest points for the input rendered image I_i .

4.2.2 Descriptor Loss

SuperPoint's [6] loss consists of an interest point detection loss \mathcal{L}_p and a descriptor loss \mathcal{L}_d .

The interest point detection loss is a cross-entropy loss between the interest point detector prediction \mathcal{X} on the input image, and the ground truth interest points \mathcal{Y} . We effectively do not apply any modifications to the interest point detection loss.

SuperPoint's [6] descriptor loss \mathcal{L}_d , is a hinge loss between every pair of descriptors cells, $d_{hw} \in \mathcal{D}$ from \mathcal{I} and $d_{h'w'} \in \mathcal{D}'$ from \mathcal{I}' . "Cells" are essentially pixels in the lower dimension feature map, for an input image of size $H \times W$, the feature map has a dimension of $H_c = \frac{H}{8} \times W = \frac{W}{8}$. In simpler terms, each pixel in the encoded image maps an 8×8 region of the input image. SuperPoint's descriptor loss \mathcal{L}_d can be defined as:

$$\mathcal{L}_d(D, D', S) = \frac{1}{(H_c W_c)^2} \sum_{\substack{h=1\\w=1}}^{H_c, W_c} \sum_{\substack{h'=1\\w'=1}}^{H_c, W_c} l_d(d_{hw}, d'_{h'w'}; s_{hwh'w'})$$
(3)

where l_d is defined as:

$$l_d(d, d'; s) = \lambda_d * s * max(0, m_n - d^T d') + (1 - s) * max(0, d^T d' - m_n)$$
(4)

where m_p is the hinge loss's positive margin, m_n is the negative margin and λ_d balances between the positive and negative correspondences. Additionally, S in Eq. 3 is a homography-induced correspondence, defined as:

$$s_{hwh'w'} = \begin{cases} 1, & \text{if } ||\widehat{\mathcal{H}p_{hw}} - p_{h'w'}|| \le \epsilon_s. \\ 0, & \text{otherwise} \end{cases}$$
 (5)

where p_{hw} is the centre pixel in the (h, w) cell, and $\widehat{\mathcal{H}p_{hw}}$ is multiplying the centre pixel cell p_{hw} by a homography \mathcal{H} which relates the input image and its warped pair.

We reformulate the homography-induced correspondence of SuperPoint [6], in such a way that centre pixel p_{hw} can be transformed using the PrP process rather than transforming it through homography \mathcal{H} . Let $\mathcal{C}(\cdot)$ represent a function that takes p_{hw} as an input, along with all parameters utilised in the PrP process (see Eqs. 1 and 2), for simplicity, these parameters can be combined and denoted as M. Therefore, the PrP-induced correspondence can be defined as:

$$s_{hwh'w'} = \begin{cases} 1, & \text{if } ||\mathcal{C}(M; p_{hw}) - p_{h'w'}|| \le \epsilon_s. \\ 0, & \text{otherwise} \end{cases}$$
 (6)

4.3 Implementation details

For all experiments, we present results using our training pipeline for both SuperPoint-PrP and SiLK-PrP. Additionally, both SuperPoint-PrP and SiLK-PrP were trained exclusively on the NeRF dataset. Furthermore, we report results for the baseline SuperPoint[6] model using our own reproduced implementation, which closely follows the training hyperparameters of the public version of SuperPoint [39].

To mitigate misprojection errors during the PrP process, we employ a random sampling approach for selecting image $I^{'}$ from a subset of the training data. This subset is constrained within a range determined by a lower limit, λ_l , and an upper limit, λ_u , based on the input image I. Specifically, we set λ_l to 70 and λ_u to 150, ensuring a balance between viewpoint changes while avoiding projection errors. Moreover, the depth window estimation process threshold ϵ_d was set as $3e^{-2}$ meters.

Additionally, for SuperPoint-PrP and SiLK-PrP training, we apply the same photometric augmentation applied on the baseline models [6, 14] such as random brightness and contrast, Gaussian noise, motion blur, but do not apply homographic augmentation such as rotation, scaling or translation. Lastly, all models are trained using PyTorch [40] and a single NVIDIA RTX 3090 Ti GPU.

4.3.1 SiLK-PrP training.

SiLK-PrP is trained on the NeRF dataset in an end-to-end manner for a total of 100,000 iterations. We keep the same SiLK hyperparameters when training SiLK-PrP with ADAM optimiser, a learning rate of $1e^{-4}$ and betas as (0.9, 0.999), while the batch size was set as 1.

4.3.2 SuperPoint-PrP training.

Similar to SuperPoint's baseline training pipeline, we obtain the base MagicPoint model by conducting training on the Synthetic Shapes dataset for 200,000 iterations. The MagicPoint model is identical to the SuperPoint model omitting the descriptor head, while the Synthetic Shapes dataset consists of synthetic 2D geometrical shapes such as lines, triangles and cubes.

To produce the MagicPoint-PrP model, we further train the base MagicPoint model through two rounds of Projective Adaptation on the NeRF dataset, each lasting 30,000 iterations. Finally, the SuperPoint-PrP model is obtained by training both the detector and descriptor heads of MagicPoint-PrP once again on the NeRF dataset for a total of 300,000 iterations. The training process is performed using the baseline SuperPoint model hyperparameters with ADAM optimiser, a learning rate of $1e^{-3}$ and betas set to (0.9, 0.999). The batch size is set at 32 for the MagicPoint-PrP model and 2 for the SuperPoint-PrP model. Lastly, for the Baseline SuperPoint model, the default and optimum homography-induced correspondence threshold ϵ_s in Eq. 5 is 8. However, experiments showed that the optimum PrP-induced correspondence threshold ϵ_s in Eq. 6 is 4.

5 Experiments

In this section, we assess the performance of PrP-supervised models compared to their corresponding baselines. Evaluations include interest point detection quality and homography estimation on HPatches [41], indoor relative pose estimation and point cloud registration on ScanNet [15], and outdoor relative pose estimation on YFCC100M and MegaDepth [16, 17]. For all evaluations, we use mutual nearest neighbour for feature matching. Through these experiments, we analyse the following:

- Our NeRF dataset is approximately $\frac{1}{30}$ the size of the MS-COCO dataset [20], and $\frac{1}{250}$ the size of ScanNet's [15]. Despite the relatively small scale of our training dataset, we analyse the generalisability of the NeRF-trained models on real-world data and various conditions across multiple datasets. Surprisingly, the PrP models trained on our NeRF datasets consistently demonstrate comparable results in most evaluations. This raises the question of the necessity for large open-source datasets in training learning-based detectors and descriptors.
- Unlike [20, 15, 17, 42], our NeRF dataset consists entirely of synthetic images. We assess the interest point
 detection quality of the NeRF-trained detectors against their baselines. Experiments revealed that the quality
 of interest points generated by NeRF-trained models remained consistently high, showing no degradation
 compared to the baseline models.
- As we explicitly render each scene in our NeRF dataset from various viewpoints, simulating real camera motion instead of relying on homography to mimic camera motions, we explore whether models supervised by the PrP process demonstrate improvement in their relative pose estimation capabilities. Additionally, we assess whether PrP-supervised models require fewer iterations during training compared to the homography-supervised baselines. Results show that not only do the PrP-supervised models exhibit enhancement in relative pose estimation but also converge faster (*i.e.* SiLK-PrP converged in approximately 27K iterations compared to 50K for SiLK).

5.1 Homography Estimation

Following [24, 6, 23, 14, 7] we evaluate homography estimation on the HPatches dataset [41]. The HPatches dataset consists of 57 scenes with varying illumination and 59 scenes with large viewpoint variations. Each scene contains 6 images, related by ground truth homographies.

5.1.1 Evaluation Protocol.

We follow [24, 14] and resize the shorter image side to a dimension of 480. To evaluate interest point detection quality and performance, we report the repeatability metric as in [6, 14]. Moreover, we evaluate the keypoint descriptors, we report the mean matching accuracy (MMA) *i.e.* the ratio of matches where reprojection error is below a specified threshold [21], and matching score *i.e.* The ratio between correctly matched points and a total number of detected

Table 1: **HPatches Metrics.** Both baseline SiLK [14] and SuperPoint [6], surpass SiLK-PrP and SuperPoint-PrP on HPatches metrics.

	Rep. ↑		Hom. Est. Acc. ↑		Hom. E	Est. AUC↑	MM	MS ↑	
	$\epsilon = 3$	$\epsilon = 5$	$\epsilon = 3$	$\epsilon = 5$	$\epsilon = 3$	$\epsilon = 5$	$\epsilon = 3$	$\epsilon = 5$	
SP	0.58	0.67	0.81	0.87	0.55	0.67	0.68	0.73	0.52
SP-PrP-Hyb	0.58	0.70	0.79	0.87	0.51	0.64	0.68	0.75	0.55
SP-PrP	0.53	0.67	0.75	0.84	0.45	0.60	0.65	0.73	0.51
SiLK	0.77	0.85	0.84	0.90	0.65	0.74	0.66	0.67	0.38
SiLK-PrP	0.72	0.80	0.75	0.81	0.54	0.64	0.62	0.63	0.31
SiLK-PrP-Aug	0.74	0.82	0.78	0.85	0.56	0.67	0.60	0.61	0.32

Table 2: **HPatches metrics separated.** SiLK-PrP and SiLK are similar in estimating homography for scenes with varying viewpoints, while SiLK-PrP falls behind in varying illumination scenes.

		HPatch	es Viewp	oint	HPatches Illumination					
	Rej	p. ↑	Hom. I	Est. Acc. ↑	Rej	p. ↑	Hom. Est. Acc. ↑			
	$\epsilon = 3$	$\epsilon = 5$	$\epsilon = 3$ $\epsilon = 5$		$\epsilon = 3$	$\epsilon = 5$	$\epsilon = 3$	$\epsilon = 5$		
SiLK	0.79	0.86	0.73	0.84	0.75	0.84	0.95	0.96		
SiLK-PrP-Aug	<u>0.79</u>	<u>0.87</u>	0.71	0.81	0.69	0.77	0.87	0.89		

points. Lastly, we use OpenCV's RANSAC algorithm to estimate the homography between an image pair and report the homography estimation accuracy and area under the curve (AUC) error over all image pairs. We keep the top 1k detected interest points for SuperPoint and 10k for SiLK.

5.1.2 Baselines.

We assess SuperPoint-PrP by comparing it to the baseline SuperPoint model [6]. Additionally, we introduce a hybrid variant of SuperPoint-PrP denoted as "SP-PrP-Hyb". This variant incorporates the MagicPoint model, trained through two rounds of Homographic Adaptation, followed by training the SuperPoint model on the NeRF dataset using our PrP process and Projective Adaptation. Furthermore, we present two versions of PrP SiLK models; the first, SiLK-PrP, is trained without rotation or scaling augmentation as detailed in Sec. 4.1. The second, SiLK-PrP-Aug, includes rotation and scaling augmentations during training.

5.1.3 Results.

As seen in Tab. 1, the PrP-supervised models are outperformed by their baseline counterparts [14, 6] in all of the HPatches metrics. Nonetheless, this outcome is expected as both SiLK-PrP and SuperPoint-PrP are not rotation or scale-invariant, in contrast to their corresponding baseline models. On the other hand, despite SiLK-PrP-Aug's efforts to incorporate in-place augmentation for rotation and scale invariance (see Fig. 3), it falls short compared to the SiLK model.

Tab. 2 further delves into SiLK-PrP-Aug's homography estimation performance, revealing its homography estimation aligns with SiLK in scenes with varying viewpoints. However, a dip in performance is observed in scenes with varying illumination conditions. This discrepancy contributes to the observed performance gap between SiLK-PrP-Aug and SiLK [14] in Tab. 1. We opted to use the same photometric augmentation used for SiLK [14] when training SiLK-PrP and SiLK-PrP-Aug, however, optimising photometric augmentation parameters during training SiLK-PrP and SiLK-PrP-Aug on the NeRF dataset might offer improved results.

5.2 Relative Pose Estimation

We leverage the ScanNet dataset [15] to evaluate the relative pose estimation on indoor scenes. We employ the 1500 test image pairs provided by [23].

We employ the YFCC100M [16] and MegaDepth [17] datasets to assess pose estimation on outdoor scenes. We utilise the YFCC100M test split introduced by [23], this split samples 1000 image pairs from four scenes each, thus, the total number of image pairs for the outdoor pose evaluation is 4000 image pairs. Additionally, we use the MegaDepth1500 test split introduced by [21, 24]. This test split comprises 1500 image pairs from two phototourism scenes: "Sacre Coeur" and "St. Peter's Square".

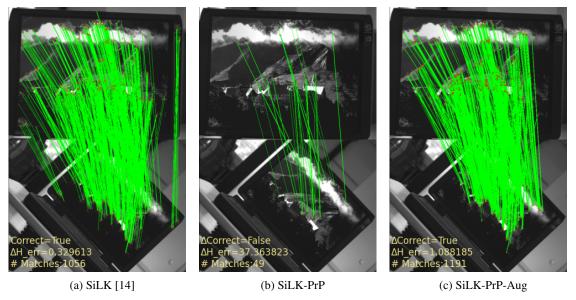


Figure 3: **Rotation and Scale invariance.** In Fig. 3b, it is evident that SiLK-PrP lacks rotation and scale invariance compared to SiLK (see Fig. 3a) [14]. Incorporating rotation and scaling SiLK-PrP's training process, rotation and scale invariance is achieved (see Fig. 3c).

5.2.1 Evaluation Protocol.

For indoor relative pose evaluation, we follow [24, 23] and resize ScanNet's images to a size of $[640 \times 480]$. For SuperPoint, we use the top 1k predicted points and 20k for SiLK.

Additionally, for outdoor relative pose evaluation, we resize the YFCC100M and MegaDepth1500 images so that the longest dimension is equal to 1200 and 1600 respectively. We use the top 2k predicted points for SuperPoint and 20k for SiLK.

For both indoor and outdoor pose evaluations, we report the pose error AUC at thresholds $(5^{\circ}, 10^{\circ}, 20^{\circ})$, where the pose error is the maximum between the angular rotation error and angular translation error. Furthermore, we compute the essential matrix using the matched interest points using OpenCV with a RANSAC threshold of 0.5 over the mean of the focal length.

5.2.2 Baselines.

Similar to the Homography Estimation evaluation Sec. 5.1, we compare SuperPoint-PrP and SuperPoint-PrP-Hyb with the baseline SuperPoint model. Likewise, we assess SiLK-PrP and SiLK-PrP-Aug against the baseline SiLK model.

5.2.3 Indoor Pose Estimation Results.

As depicted in Tab.3, the PrP models consistently surpass their respective baseline counterparts across all angular pose error thresholds. Although performance enhancement for SuperPoint-PrP and SuperPoint-PrP-Hyb over SuperPoint [6] is marginal, a more substantial improvement is evident in the case of SiLK-PrP and SiLK-PrP-Aug in comparison to SiLK [14], particularly as the angular threshold increases.

Unfortunately, the relative pose estimation computes the translation error as the angular translation error between the ground truth and estimated translation vectors. The computed angular translation error suffers from instability as it could only be computed up to a certain scale factor [43, 44]. This instability could be seen in Fig. 4, where it is evident that the angular translation error is unstable when the norm of the ground truth relative translation vector ($||t_{GT}||$) is approximately 0.2 and below.

To address this issue, we refined the indoor relative pose estimation assessment. For scenes where $||t_{GT}||$ is below the threshold ϵ set at 0.15, we exclusively report the pose error AUC based on angular rotation error. Furthermore, for scenes where the threshold ϵ exceeds 0.15, we report the pose error AUC as the maximum value between angular rotation and translation errors. As presented in Tab. 4, it is evident that all models excel in estimating relative rotation in scenes characterised by minimal translation between viewpoints. Notably, the PrP models exhibit a slight performance

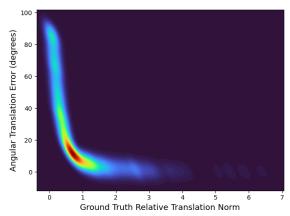


Figure 4: **Instability in Angular Translation Error.** Density plot illustrating how the angular translation error is unstable in situations where the ground truth relative translation between two camera viewpoints is minimal.

Table 3: **Indoor Relative Pose Estimation Error AUC.** The models trained using the PrP process outperform their respective baseline models [14, 6] in accurately estimating relative poses within indoor scenes for all reported angular thresholds.

Pose Est. AUC	@5° ↑	@10° ↑	@20° ↑
SP	7.56	17.76	30.43
SP-PrP-Hyb	<u>7.82</u>	<u>17.85</u>	31.08
SP-PrP	7.73	17.72	30.71
SiLK	7.18	16.14	27.84
SiLK-PrP	9.42	20.17	32.31
SiLK-PrP-Aug	<u>9.60</u>	<u>20.75</u>	<u>34.24</u>

Table 4: **Separated Indoor Relative Pose Estimation Error AUC.** For image pairs with minimal relative translation in viewpoints, the PrP models exhibit superior performance in accurately estimating the relative rotation, especially the SuperPoint-PrP and SiLK-PrP-Aug models.

	Pose E	st. AUC t	$ t_{gt} \leq \epsilon$	Pose Est. AUC $ t_{gt} > \epsilon$						
Pose Est. AUC		Rot.,		max (Rot., Transl.),						
	15	57 image pa	airs	1363 image pairs						
	@5° ↑	@10° ↑	@20° ↑	@5° ↑	@10° ↑	@20° ↑				
SP	55.29	73.85	84.81	8.08	18.79	31.74				
SP-PrP-Hyb	<u>56.17</u>	74.21	<u>85.85</u>	8.37	18.83	32.02				
SP-PrP	53.21	73.52	85.28	8.29	18.21	30.40				
SiLK	54.33	73.02	85.24	7.62	17.02	28.82				
SiLK-PrP	57.59	74.19	85.28	10.22	21.53	33.52				
SiLK-PrP-Aug	<u>57.60</u>	<u>75.54</u>	<u>86.38</u>	<u>10.22</u>	<u>21.79</u>	<u>35.07</u>				

advantage over their baseline counterparts in this specific scenario. Additionally, in scenes where the ground truth relative translation exceeds the defined threshold, further improvement can be observed for the PrP models compared to results reported in Tab. 3.

5.2.4 Outdoor Pose Estimation Results.

Similar to results obtained in Tab. 3, the PrP models surpass their corresponding baseline models in relative pose estimation for outdoor scenes, as observed by results shown in Tabs. 5 and 6. The results reported in Tabs. 3 to 6 collectively highlight that models subjected to PrP supervision during training demonstrate significant improvement in their relative pose estimation capability.

Table 5: YFCC Relative Pose Estimation Error AUC.

Pose Est. AUC	@5° ↑	@10°↑	@20° ↑
SP	12.01	22.66	35.48
SP-PrP-Hyb	<u>14.04</u>	<u>26.53</u>	40.80
SP-PrP	12.57	23.86	37.88
SiLK	7.82	15.05	24.93
SiLK-PrP	<u>9.44</u>	<u>17.31</u>	<u>27.04</u>
SiLK-PrP-Aug	7.82	14.33	22.52

Table 6: MegaDepth Relative Pose Estimation Error AUC.

Entor Acc.			
Pose Est. AUC	@5° ↑	@10° ↑	@20° ↑
SP	25.21	39.42	52.11
SP-PrP-Hyb	<u>27.34</u>	42.64	56.03
SP-PrP	26.17	41.53	55.87
SiLK	22.70	35.32	48.08
SiLK-PrP	<u>25.91</u>	35.50	46.41
SiLK-PrP-Aug	24.79	34.38	45.00

Table 7: **Point Cloud Reg.** SuperPoint-PrP and SuperPoint-PrP demonstrate marginal enhancements over the baseline SuperPoint model. Meanwhile, SiLK-PrP and SiLK-PrP-Aug maintain competitiveness with the baseline SiLK model.

	Rot.					Transl.				Chamfer					
	Acc. ↑		Err.↓		Acc. ↑		Err. ↓		Acc. ↑			Err. ↓			
	5°	10°	45°	M.	Med.	5	10	25	M.	Med.	1	5	10	M.	Med.
SP	88.4	95.1	98.8	4.0	1.8	53.2	79.9	94.5	9.5	<u>4.7</u>	73.2	91.6	94.8	6.4	0.4
SP-PrP-Hyb	<u>88.5</u>	<u>95.9</u>	<u>99.1</u>	3.8	1.9	50.9	79.5	<u>95.5</u>	8.9	4.9	71.9	<u>92.4</u>	<u>95.6</u>	<u>5.6</u>	<u>0.4</u>
SP-PrP	88.3	<u>95.9</u>	99.1	3.8	1.9	51.4	<u>79.9</u>	95.3	9.0	4.9	72.4	92.2	95.5	<u>5.6</u>	<u>0.4</u>
SiLK	95.6	<u>97.5</u>	99.1	2.6	0.8	79.9	91.4	96.9	6.1	2.2	89.4	95.8	97.1	4.7	0.1
SiLK-PrP	93.0	96.2	98.7	3.4	1.0	71.3	87.0	95.3	8.1	2.8	84.3	93.7	95.7	5.7	<u>0.1</u>
SiLK-PrP-A.	94.6	97.2	99.0	2.8	0.9	75.0	89.5	96.4	7.0	2.5	86.8	95.1	96.7	5.4	0.1

5.3 Pairwise Point Cloud Registration

We follow recent work [45, 14] and evaluate the interest point detectors and descriptors on a 3D point cloud registration task. Evaluation is performed on ScanNet's [15] official test split, where image pairs are sampled 20 frames apart.

5.3.1 Evaluation Protocol.

The point cloud registration evaluation is conducted by resizing the ScanNet [15] images to dimensions of [128 \times 128]. Given a pair of RGB-D images, a 6-DOF pose is estimated that best aligns the first image to the second image. The metrics reported during the evaluation are angular rotation and translation errors in degrees and centimetres respectively. Moreover, the chamfer distance is also reported between the ground-truth point cloud and the reconstructed point cloud in centimetres. For all three reported metrics the accuracy, mean and median errors over the entire dataset are reported at different thresholds [45].

5.3.2 Baselines.

Unlike previous evaluations (Secs. 5.1 and 5.2) where sparse feature matching was employed, we follow [45, 14] and perform the point cloud registration using dense feature matching. The ratio test is utilised to find correspondences and alignment is seen as a Procustes problem solved by a weighted Kabsch's algorithm. [46, 47, 14].

5.3.3 Results.

As depicted in Tab. 7, both SuperPoint-PrP and SuperPoint-PrP-Hyb outperform the baseline SuperPoint model across all metrics, except for translation at a 5 cm threshold. SiLK generally maintains a 1-3% advantage over SiLK-PrP and SiLK-PrP-Aug, with a 5% lead at a 5 cm translation threshold. However, the SiLK-PrP models remain competitive with the baseline SiLK model.

It is essential to highlight that SiLK is trained on smaller images [164x164], while the NeRF dataset is comprised of larger images [640x480]. Since the point cloud registration is conducted on an image size of [128x128], SiLK may outperform SiLK-PrP at lower resolutions, however, the SiLK-PrP models still detect high-quality interest points at low resolutions.

6 Conclusion

This paper presented a novel approach to supervise feature point detectors and descriptors using perspective projective geometry on synthetic data. Despite using a smaller dataset, our PrP approach achieves similar or better performance without compromising generalisability. Moreover, we noticed that the PrP-supervised models converge faster and outperform homography-supervised models in non-planar multi-view benchmarks, though, they slightly lag in homography estimation. We emphasise the main advantage of the PrP approach is not only benchmark improvements, but also its ability to train on any custom multi-view synthetic dataset with less data and less training time. The larger potential for further advancements depends on enhancing neural rendering to produce higher-quality synthetic images and more accurate depth maps, reducing artefacts and misprojection errors.

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