Decoupling Makes Weakly Supervised Local Feature Better

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Abstract

Weakly supervised learning can help local feature methods to overcome the obstacle of acquiring a large-scale dataset with densely labeled correspondences. However, since weak supervision cannot distinguish the losses caused by the detection and description steps, directly conducting weakly supervised learning within a joint training describe-then-detect pipeline suffers limited performance. In this paper, we propose a decoupled training describe-then-detect pipeline tailored for weakly supervised local feature learning. Within our pipeline, the detection step is decoupled from the description step and postponed until discriminative and robust descriptors are learned. In addition, we introduce a line-to-window search strategy to explicitly use the camera pose information for better descriptor learning. Extensive experiments show that our method, namely PoSFeat (Camera Pose Supervised Feature), outperforms previous fully and weakly supervised methods and achieves state-of-the-art performance on a wide range of downstream task.

1. Introduction

Finding pixel correspondences is a fundamental problem in computer vision. Sparse local feature [5,12,22,36,48], as one of the mainstream methods to find correspondences, has been widely applied in many areas, such as simultaneous localization and mapping (SLAM) [29,52], structure from motion (SfM) [1,40], and visual localization [7,16,38,51].

Traditional sparse local feature methods [5,22,36] follow a detect-then-describe pipeline. Specifically, keypoints are first detected and then patches centered at these keypoints are used to generate descriptors. Early methods [15,17,19,22] focus on the detection step and are proposed to distinguish distinctive areas to detect good keypoints. Later works pay more attention to the description step and make attempts to design powerful descriptors using advanced representations [5,8,36].

Motivated by the success of deep learning, many efforts [23,27,31,44,50] have been made to replace the detection or description step in the detect-then-describe pipeline with CNNs. Recent works [13,24,34,46] find that keypoints and descriptors are interdependent and propose a joint training describe-then-detect pipeline. Specifically, the description network and detection network are combined into a single CNN and optimized jointly. The joint training describe-then-detect pipeline achieves better performance than the detect-then-describe pipeline, especially under challenging conditions [18,45]. However, these methods are fully supervised and rely on dense ground-truth correspondence labels for training.

Because collecting a large dataset with pixel-level ground-truth correspondences is expensive, self-supervised and weakly supervised learning are investigated for training. Specifically, DeTone et al. [12] used a single im-
age and a virtual homography to generate image pairs to conduct self-supervised learning. However, homography transformation cannot cover complicated geometry transformations in real-world settings, resulting in limited performance. Noh et al. [30] used landmark labels to train the local feature network, which suffers extremely poor performance on viewpoint changes. Owing to the convenience of collecting camera poses, Wang et al. [47] introduced camera poses as weak supervision for descriptor learning. Although weakly supervised learning achieves promising results within the detect-then-describe pipeline, directly applying it to the joint training describe-then-detect pipeline is hard to produce satisfying results [46].

When a detection network and a description network are jointly optimized within a joint training describe-then-detect pipeline with only weak supervision (e.g., camera pose), the loss produced by these two components cannot be distinguished. Specifically, when only one component is failed (Fig. 2), both the detection network and the description network cannot be correctly updated within a joint training describe-then-detect pipeline. As a result, the description network is hard to produce highly discriminative descriptors, and the detection network may produce false detected keypoints that are out of object boundaries, as shown in Fig. 1.

In this paper, we propose a decoupled training describe-then-detect pipeline tailored for weakly supervised local feature learning. Our main insight is that, with only weak supervision, the detection network relies heavily on a good descriptor for accurate keypoint detection (Fig. 1). Consequently, we decouple the detection network from the description network to postpone it until a discriminative and robust descriptor is learned. Different from the detect-then-describe pipeline that relies on low-level structures for early detection, our keypoints detection depends on the higher-level structures encoded in the descriptors. As a result, better robustness is achieved. In contrast to the joint training describe-then-detect pipeline that simultaneously perform detection and description optimization, the two networks are trained separately and thus the loss function for these two components are decoupled to address the ambiguity. It is demonstrated that our decoupled training describe-then-detect pipeline facilitates local feature methods to achieve much better performance with only weak supervision. Our contributions can be summarized as:

1. We introduce a decoupled training describe-then-detect pipeline for weakly supervised local feature learning. This simple yet efficient pipeline significantly improves the performance of weakly supervised local features.

2. We propose a line-to-window search strategy to exploit the weak supervision of camera poses for descriptor learning. This strategy can make full use of the geometric information of camera poses to reduce the search space and learn highly discriminative descriptors.

3. Our method achieves state-of-the-art performance on three datasets and largely closes the gap between fully and weakly supervised methods.

2. Related Works

2.1. Fully Supervised Local Feature Methods

Fully supervised methods conduct local feature learning using pixel-level ground-truth correspondences to provide supervision. Following the detect-then-describe pipeline, early learning-based methods [4,14,23,27,39,44] use CNNs to perform the detection or description steps. Specifically, QuadNet [39] and Key.Net [4] were proposed to use CNNs for keypoint detection. HardNet [27] and SOSNet [44] were developed to leverage CNNs to extract descriptors. Later, LIFT [50] and LFNet [31] were introduced to integrate both detection and description steps into an end-to-end architecture to achieve better performance. Note that, LIFT [50] also introduced a decoupled training to address unstable training issue with full supervision in a detect-then-describe pipeline.

Recent works [13, 24, 34, 46] follow a joint training describe-then-detect pipeline in which detection and description are combined into a single CNN and optimized jointly. Specifically, Dusmanu et al. [13] first used a CNN to extract dense features and then selected local maxima of the dense feature map as keypoints. Revaud et al. [34] further took both the repeatability and reliability of the descriptors into consideration for better keypoint detection. Tyszkiewicz et al. [46] used policy gradient to address the discreteness during the selection of sparse keypoints (namely, DISK). Luo et al. [24] adopted deformable convolution to model the geometry information and detected keypoints at multiple scales. By jointly optimizing the detection network and the description network, joint training describe-then-detect pipeline achieves better performance than previous detect-then-describe pipeline.
2.2. Self-Supervised Local Feature Methods

As a large dataset with densely labeled correspondences is difficult to collect, self-supervised learning has been studied for local feature learning. Specifically, DeTone et al. [12] used a virtual homography to generate an image pair from a single image to conduct self-supervised learning. This method uses a CNN pretrained on synthetic data as a teacher of the detection network. Differently, Christiansen et al. [11] proposed an end-to-end framework to train both the detection network and the description network using virtual homography in a self-supervised manner. Later, Parikh et al. [32] leveraged the homography to enhance the robustness of descriptors to rotation. Nevertheless, simple homography transformations used in these self-supervised methods may not hold in real cases.

2.3. Weakly Supervised Local Feature Methods

Noh et al. introduced DELF [30], which is trained with an image retrieval task, to achieve local feature extraction. However, the keypoints detected by DELF are sensitive to viewpoint change and thus cannot be applied in real-world settings. For camera poses are easy to collect, Wang et al. [47] used them as weak supervision and introduced an epipolar loss for descriptor learning. This method follows a detect-then-describe pipeline and relies on an off-the-shelf detection method (e.g., SIFT) to detect keypoints. Recently, Tyszkiewicz et al. [46] developed DISK-W to integrate weakly supervised learning in a joint training describe-then-detect pipeline by adopting policy gradient. Nevertheless, when DISK-W is directly trained with a weakly supervised loss (rather than a fully-supervised loss), it suffers a notable performance drop on pixel-wise metrics. As weakly supervised loss cannot distinguish between errors introduced by false keypoints and inaccurate descriptors, this ambiguity hinders the joint training describe-then-detect pipeline to learn good local features.

2.4. Learning-based Matcher Methods

Since a Brute Force Matcher (also named NN matcher) usually produces low quality raw matches, learning-based matchers are proposed to achieve better matching results. Sarlin et al. [37] proposed SuperGlue to achieve robust matching with a graph neural network (GNN) and an optimal transport algorithm. Chen et al. [10] improved the architecture of GNN to increase the efficiency of descriptor enhancement. Zhou et al. [53] proposed a weakly supervised network to refine raw matches using patch matches as prior. Sun et al. [42] introduced a detector-free matcher to achieve pixel correspondence in a coarse-to-fine manner. Note that, most matcher methods are not the direct competitors of local feature methods. Instead, they can be considered as a post-processing step and combined with local features to achieve improved performance.

3. Decoupled Training Describe-then-Detect Pipeline

3.1. Overview

The decoupled training describe-then-detect pipeline is shown in Fig. 3. We train the description net and detection net individually to suppress the loss ambiguity caused by weak supervision. During training, we first leave out the detection network and optimize the description network to learn good descriptors with a line-to-window strategy. The description network is then frozen to train a detection network for keypoint detection. We follow CAPS [47] to use ResUNet as the description net, which produces a feature map with 1/4 resolution and 128 dimensions as dense descriptors. Additionally, we design a shallow detection net to detect keypoints at the original resolution. For more details about the network architecture, please refer to the supplementary material.
3.2. Feature Description

Following the widely used paradigm [47], we impose supervision only on sparse query points sampled from paired images to conduct training of the description network. We first split an image into small grids of size $g_1 \times g_2$, and randomly sample one point per grid as a query point. Then, we translate relative camera pose into an epipolar constraint and introduce a line-to-window search strategy to reduce search space (Sec. 3.2.1). Moreover, we formulate a loss function by encouraging the predicted matches to obey the epipolar constraint (Sec. 3.2.2).

3.2.1 Line-to-Window Search

Given a query point $x_i$ in the query image $I_1$, our goal is to find its correspondence in the reference image $I_2$. Since repetitive structures widely exist in a natural image, the commonly used coarse-to-fine strategy [42, 47] usually selects a mismatched patch such that inferior performance is produced (Fig. 4(a)). Intuitively, the correspondence of the query point $x_i$ is constrained in an epipolar line in the reference image. Therefore, we introduce a line-to-window search strategy to reduce search space for better performance. Our line-to-window search strategy consists of two search steps, as illustrated in Fig. 4(b).

**Search along An Epipolar Line.**

For a query point $x_i \in I_1$, we first calculate its corresponding epipolar line $L_x$, in the reference image $I_2$ based on the relative camera pose. Then, we uniformly sample $N_{line}$ points along this epipolar line to formulate the search space $Y_{line} = \{y_i^j\} (j = 1, ..., N_{line})$. Next, we calculate the matching probability of $x_i$ over $Y_{line}$:

$$P(y_i^j | F_1(x_i), F_2(Y_{line})) = \frac{\exp(F_1(x_i)^T F_2(y_i^j))}{\sum_{y_i^{j'} \in Y_{line}} \exp(F_1(x_i)^T F_2(y_i^{j'}))},$$

where $F_1$ and $F_2$ are the feature maps for $I_1$ and $I_2$, respectively. Afterwards, we select $y_i$ with the maximum probability from $Y_{line}$ to determine the coarse location of the correspondence of $x_i$:

$$y_i = \arg \max_{y_i^j} P(y_i^j | F_1(x_i), F_2(Y_{line})).$$

**Search in A Local Window.**

Due to the discreteness of the candidates in $Y_{line}$, the resultant corresponding point $y_i$ can be far from the groundtruth. To remedy this, a subsequent search is conducted in a local window. First, we calculate the center of the local window:

$$y_i^{center} = y_i + 0.5 \cdot w_{patch} \cdot u,$$

where $w_{patch}$ is the window size of a local patch, $u \in \mathbb{R}^2$ is a noise vector drawn from a uniform distribution $U(0, 1)$ to avoid the convergence to trivial solution $F(x) \equiv 0$. Then, a local patch $Y_{patch} \subset I_2$ centered at $y_i^{center}$ is cropped from $I_2$ as the search space. Next, we calculate the matching probability of $x_i$ over $Y_{patch}$:

$$P(y_i^j | F_1(x_i), F_2(Y_{patch})) = \frac{\exp(F_1(x_i)^T F_2(y_i^j))}{\sum_{y_i^j \in Y_{patch}} \exp(F_1(x_i)^T F_2(y_i^j))}. $$

(4)

Because directly selecting the point with the maximum probability in the local patch is non-differentiable, we calculate the correspondence $\hat{y}_i$ in a differentiable manner:

$$\hat{y}_i = E(y_i^j) = \sum_{y_i^j \in Y_{patch}} y_i^j \cdot P(y_i^j | F_1(x_i), F_2(Y_{patch})).$$

(5)

Compared to the previous coarse-to-fine search strategy [47], our line-to-window search strategy can make better use of the camera pose information to reduce search space and further improve the discriminativeness of descriptors (as demonstrated in Sec. 4.3).
3.2.2 Loss Function
With only weak supervision of camera pose, we calculate the distance of the correspondence \( \hat{y}_i \) to the epipolar line \( L_{x_i} \), as the loss of query point \( x_i \) [47]:
\[
\mathcal{L}_{epi}(\hat{y}_i, x_i) = \text{distance}(\hat{y}_i, L_{x_i}).
\] (6)

Then, we use the weighted sum of the losses over all query points as the final loss:
\[
\mathcal{L}_{desc} = \frac{\sum_i M_i \sigma(x_i) \cdot \mathcal{L}_{epi}(\hat{y}_i, x_i)}{\sum_i M_i \sigma(x_i)}. 
\] (7)

Here, \( M_i \) is a binary mask (which is used to exclude query points whose epipolar lines are not in the reference image) and \( \sigma(x_i) \) is the variance of the probability distribution over \( Y_{\text{patch}} \):
\[
\sigma(x_i) = \| y_i^2 - E(y_i^2) \|. 
\] (8)

3.3. Feature Detection

After feature description learning, the description network is frozen to produce dense descriptors for keypoint detection, as shown in Fig. 3. Since selecting discrete sparse keypoints is non-differentiable, we adopt the strategy introduced in DISK [46], which is based on policy gradient, to achieve network training.

First, dense descriptors \( F_1 \) and \( F_2 \) are respectively extracted from \( I_1 \) and \( I_2 \), and fed to a detection network to produce keypoint heatmaps. Then, we divide these heatmaps into grids of size \( g_k \times g_k \) and select at most one keypoint from each grid cell. Specifically, we establish a probability distribution \( P_{kp} \) over each grid cell based on the heatmap scores in this cell. Afterwards, \( P_{kp} \) is used to probabilistically select candidate keypoints \( Q_1 = \{x_1, x_2, \cdots \} \) and \( Q_2 = \{y_1, y_2, \cdots \} \) from \( I_1 \) and \( I_2 \), respectively. Next, a matching probability \( P_m \) is calculated based on the feature similarity \( S_{ij} \) between each pair of candidate keypoints \( (x_i, y_j) \). With only camera pose supervision, we adopt an epipolar reward similar to Eq. 6 to encourage \( y_j \) to be close to the epipolar line of \( x_i \) (i.e., \( L_{x_i} \)):
\[
\mathcal{R}(x_i, y_j) = \begin{cases} 
\lambda_p, & \text{if distance}(y_j, L_{x_i}) \leq \epsilon, \\
\lambda_n, & \text{if distance}(y_j, L_{x_i}) > \epsilon,
\end{cases}
\] (9)

where the reward threshold \( \epsilon \) is empirically set to 2. The overall loss function is defined as:
\[
\mathcal{L}_{kp} = -\frac{1}{|Q_1| + |Q_2|} \left( \sum_{x_i, y_j} \mathcal{L}_{rew}(x_i, y_j) + \lambda_{\text{reg}} \left( \sum_{x_i} \log P_{kp}(x_i) + \sum_{y_j} \log P_{kp}(y_j) \right) \right),
\] (10)

where \( \lambda_{\text{reg}} \) is a regularization penalty and the reward loss \( \mathcal{L}_{rew}(x_i, y_j) \) is defined as:
\[
\mathcal{L}_{rew}(x_i, y_j) = P_m(x_i, y_j) \cdot R(x_i, y_j) \cdot \log(P_{kp}(x_i) P_{kp}(y_i)).
\] (11)

Since our descriptors are well optimized, \( P_m \) can suppress spurious points with low scores. In contrast, in a joint pipeline, descriptors are under-optimized such that spurious points cannot be well distinguished. Please refer to the supplementary material for more details.

4. Experiments

4.1. Experimental Settings

Datasets The MegaDepth dataset [21] was used for training. We used a subset of the training split of CAPS [47]. Totally, 127 out of 196 scenes were used as the training set.

Implementation Details During the training phase, images were resized to \( 640 \times 480 \) with breaking the aspect ratio. All networks were trained using a SGD optimizer with nesterov momentum [43]. The learning rate is set to \( 1 \times 10^{-3} \) and the batch size was set to 6. The description network was trained for 100,000 iterations, and the detection network was trained for 5,000 iterations. All experiments were conducted using Pytorch on a single NVIDIA RTX3090 GPU.

In our experiments, the number of sampled points \( N_{\text{line}} \) was set to 100, the window size \( w_{\text{patch}} \) was set to 0.1 (normalized height and width), and the grid size \( g_t \) and \( g_k \) were set to 16 and 8, respectively. Following [46], \( \lambda_p, \lambda_n, \) and \( \lambda_{\text{reg}} \) were set to 1, -0.25, and -0.001, respectively. For more details, please refer to the supplementary material.

4.2. Comparison with Previous Methods

4.2.1 Feature Matching

Settings. We first evaluate our method on the widely used HPatches dataset [3]. Following D2-Net [13], 8 high-resolution scenes are removed and the remaining 52 scenes with illumination changes and 56 scenes with viewpoint changes are included for evaluation. Mean matching accuracy (MMA) [13] with thresholds ranging from 1 to 10 is used for evaluation. We also use a weighted sum of MMA at different thresholds for overall evaluation:
\[
\text{MMAScore} = \frac{\sum_{\text{thr}[1,10]}(2 - 0.1 \cdot \text{thr}) \cdot \text{MMA@thr}}{\sum_{\text{thr}[1,10]}(2 - 0.1 \cdot \text{thr})}.
\] (12)

Three families of methods are included for comparison:

- Patch-based methods: Hessian-Affine keypoints [26] with Root-SIFT [2] (Hes. Aff. + Root-SIFT), affine region detector HesAffNet [28] with HardNet++ [27] (HAN + HN++), and SIFT [22] with ContextDesc [23] (SIFT + ContextDesc).
### Methods

| Feature | Num. | Match |
|---------|------|-------|
| Hes. Aff. + Root-SIFT | 6710 | 2851 |
| HAN + HN++ | 3860 | 1960 |
| SIFT + ContextDesc | 4066 | 1744 |
| D2-Net | 2994 | 1182 |
| R2D2 | 4996 | 1850 |
| ASLFeat | 4013 | 2009 |
| DISK | 7705 | 3851 |
| DELF | 4590 | 1940 |
| SuperPoint | 1562 | 883 |
| SIFT + CAPS | 4386 | 1450 |
| DISK-W | 6760 | 3976 |
| PoSFeat (Ours) | 8192 | 4275 |

Figure 5. Results achieved on the HPatches dataset [3]. Mean match accuracy (MMA) achieved at different thresholds are illustrated. Learning based methods with weak supervision are shown in solid lines while other methods are shown in dashed lines. The numbers of keypoints and matches for each method are also reported.

![Image pairs](a) Image pairs (b) SIFT + CAPS (c) DISK-W (d) PoSFeat (Ours)

### Visual Localization

#### Settings

We then evaluate our method on the visual localization task with the Aachen Day-Night dataset [51]. We adopt the official visual localization pipeline1 used in the local feature challenge of workshop on long-term visual localization under changing conditions. This challenge only evaluates the pose of night-time query images. Accuracy with different thresholds are used as metrics, including

1https://github.com/tsattler/visuallocalizationbenchmark/tree/master/local_feature_evaluation

#### Results

Table 1. MMAscore results achieved by different methods on the HPatches dataset [3]. The MMAscores are calculated from Fig. 5.

| Methods           | MMAscore Overall | MMAscore Illumination | MMAscore Viewpoint |
|-------------------|------------------|-----------------------|--------------------|
| Hes. Aff. + Root-SIFT [2] | 0.584 | 0.544 | 0.624 |
| HAN [28] + HN++ [27] | 0.633 | 0.634 | 0.633 |
| SIFT [22] + ContextDesc [23] | 0.636 | 0.613 | 0.657 |
| D2-Net [13] | 0.519 | 0.605 | 0.440 |
| R2D2 [34] | 0.695 | 0.727 | 0.665 |
| ASLFeat [24] | 0.739 | 0.795 | 0.687 |
| DISK [46] | 0.763 | 0.813 | 0.716 |
| DELF [30] | 0.571 | 0.903 | 0.262 |
| SuperPoint [12] | 0.658 | 0.715 | 0.606 |
| SIFT [22] + CAPS [47] | 0.699 | 0.764 | 0.639 |
| DISK-W [46] | 0.719 | 0.803 | 0.649 |
| PoSFeat (Ours) | 0.775 | 0.826 | 0.728 |

4.2.2 Visual Localization

#### Settings

As shown in Fig. 5 and Table 1, the proposed PoSFeat outperforms all previous works, with the highest MMAscore being achieved. Compared to existing weakly supervised methods, our method produces significant performance improvements. Specifically, our method outperforms DISK-W by notable margins under both illumination (0.826 vs. 0.803) and viewpoint (0.728 vs. 0.649) changes, and therefore achieves higher overall MMAscore (0.775 vs. 0.719). We also visualize the matching results in Fig. 6. It can be seen that our PoSFeat produces more reasonable keypoints and less wrong matches. Compared to fully supervised methods, our method still performs favorably with higher MMA scores. This clearly demonstrates the superiority of our method. Note that, because DELF detects keypoints in a low resolution feature map with a fixed grid, it produces the best results under illumination change. However, our method significantly surpasses DELF under viewpoint change (0.728 vs. 0.262) and achieves much better overall performance (0.775 vs. 0.571).
### Table 2. Results achieved by different methods on the Aachen Day-Night dataset [51]. ‘LISRD’ represents LISRD with Super-Point keypoints and AdaLAM [9]. Two categories of methods are presented, including feature methods (top) and matchers (bottom).

| Method                | Aachen Day-Night v1 | Aachen Day-Night v1.1 |
|-----------------------|---------------------|-----------------------|
|                        | (0.5m, 2°) | (1m, 5°) | (5m, 10°) | (0.5m, 2°) | (1m, 5°) | (5m, 10°) |
| SP [12]                | 74.5 | 78.6 | 89.8 | - | - | - |
| D2-Net [13]           | 74.5 | 86.7 | 100 | - | - | - |
| R2D2 [34]             | 76.5 | 90.8 | 100 | 71.2 | 86.9 | 97.9 |
| ASLFeat [24]          | 81.6 | 87.8 | 100 | - | - | - |
| ISRF [23]             | - | - | - | 69.1 | 87.4 | 98.4 |
| LISRD [33]            | - | - | - | 72.3 | 86.9 | 97.9 |
| PoSFeat (Ours)        | 81.6 | 90.8 | 100 | 73.8 | 87.4 | 98.4 |
| DualRC-Net [20]       | - | - | - | 71.2 | 86.9 | 97.9 |
| SP+SuperGlue [37]     | 79.6 | 90.8 | 100 | 73.3 | 88.0 | 98.4 |
| SparseNCNet [35]      | 76.5 | 84.7 | 98.0 | - | - | - |
| LoFTR [42]            | - | - | - | 72.8 | 88.5 | 99.0 |
| Patch2Pix [53]        | 79.6 | 87.8 | 100 | - | - | - |
| SP+SGMNet [10]        | 77.6 | 88.8 | 99.0 | 72.3 | 85.3 | 97.9 |

We compare our method with two families of methods:

- **Local feature methods**: D2-Net [13], SuperPoint [12], R2D2 [34], ASLFeat [24], ISRF [25], and LISRD [33].
- **Matcher methods**: DualRC-Net [20], SuperGlue [37] + SuperPoint, SparseNCNet [35], LoFTR [42], Patch2Pix [53], and SGMNet [10] + SuperPoint. As mentioned in Sec 2.4, matchers are the cooperators instead of the direct competitors of local features. Therefore, we group them separately.

**Results.** As shown in Table 2, our PoSFeat achieves the state-of-the-art performance among the feature methods. Specifically, on Aachen Day-Night v1, our method achieves the best accuracy in terms of all metrics. Note that, although ASLFeat is a fully supervised method, our PoSFeat still outperforms it on (1m, 5°). On Aachen Day-Night v1.1, our method also produces the best performance in all accuracy metrics. Note that, although R2D2 [34], ISRF [25], and LISRD [33] are fully-supervised and trained on the Aachen Day-Night dataset, our PoSFeat still achieves better results. We additionally include matcher methods for further comparison. Although these methods take pairs of images as inputs, our PoSFeat achieves comparable or even better performance.

4.3. Ablation Study

In this section, we first conduct ablation experiments on the HPatches dataset [3] to demonstrate the effectiveness of our **decoupled training describe-then-detect** pipeline and line-to-window search strategy. Then, we conduct experiments to study the effectiveness of hyper-parameters in our method, i.e., the number of points sampled from the epipolar line \( N_{line} \) and the window size \( w_{patch} \). Results and model settings are shown in Fig. 7 and Table 4.

**Decoupled Training Describe-then-Detect Pipeline.** We first constructed a network variant (Model 2) following the joint training describe-then-detect pipeline. That is, the description network and the detection network are jointly op-
In this paper, we introduce a decoupled training describe-then-detect pipeline tailored for weakly supervised local feature learning. Within our pipeline, the detection network is decoupled from the description network and postponed until discriminative and robust descriptors are obtained. In addition, we propose a line-to-window search strategy to explicitly use the camera pose information to reduce search space for better descriptor learning. Extensive experiments show that our method achieves the state-of-the-art performance on three different evaluation frameworks and significantly closes the gap between fully-supervised and weakly supervised methods.

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| Model | descriptor | keypoint training |
|-------|------------|-------------------|
| 1 (full) | L2W learned | decoupled |
| 2 | L2W learned | joint |
| 3 | L2W SIFT | - |
| 4 | C2F SIFT | - |
| DISK-W | weakly supervised DISK model |

| Model | descriptor | keypoint |
|-------|------------|----------|
| 5 | PoSFeat | PoSFeat |
| 6 | PoSFeat | DISK-W |
| 7 | DISK-W | PoSFeat |
| 8 | DISK-W | DISK-W |

Figure 7. Ablation results on HPatches. “L2W” denotes our line-to-window search strategy (illustrated in Fig 4(b)) and “C2F” denotes the coarse-to-fine search strategy [47] (illustrated in Fig 4(a)). “learned” means that the keypoints are generated by a detection network and “SIFT” mean that SIFT keypoints (OpenCV default settings) are used. “decoupled” means the proposed decoupled training pipeline is adopted and “joint” means the description network and the detection network are jointly optimized.

Table 4. MMAscore achieved by our description network with different values of $N_{line}$ and $w_{patch}$ on the HPatches dataset.

| $N_{line}$ | $w_{patch}$ | 0.075 | 0.100 | 0.125 |
|------------|-------------|-------|-------|-------|
| 75         | 0.7703      | 0.7735 | 0.7666 |
| 100        | 0.7726      | 0.7748 | 0.7732 |
| 125        | 0.7732      | 0.7745 | 0.7744 |
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Supplementary Material for
Decoupling Makes Weakly Supervised Local Feature Better
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We first introduce the details of our model in Sec. 1 and discuss the query points generation during description network training in Sec. 2. Then, we expand the detection network training in Sec. 3. Next, we show detailed experimental settings in Sec. 4. After that, we give a discussion on the limitations and broader impact of our PoSFeat in Sec. 5. Finally, additional qualitative results are included in Sec. 6.

1. Model Architecture

Our model consists of two parts, i.e. the description network and the detection network, as illustrated in Fig. 1. For description network, we adopt the ResUNet used in [9], which follows a widely used encoder-decoder architecture. We use a truncated ResNet-50 [4] (pre-trained on ImageNet [2]) as the encoder, and use several $3 \times 3$ convolution layers combining with bilinear upsampling and residual connection to construct the decoder. For detection network, we use a simple three-layer architecture. The first layer takes the original image and two feature maps from description network as inputs, and aggregate the original image and feature maps from description network for detection. For better aggregation of original image and feature maps, we use the instance normalization [8] instead of batch normalization [5] in our detection network.

2. Query Points Generation in Description Network Training

We adopt grid-based random sampling to select query points for the training of description network to avoid the bias of pre-defined keypoints. When pre-defined keypoints (e.g. SIFT) are used to train the description network, the densities of SIFT keypoints in different areas vary a lot.

Figure 1. Model architecture. The description network (a) and detection network (b) consist of several blocks, we report the scale and output channels of each block, and illustrate the details of each block in the bottom box.
Figure 2. An illustration of pre-defined keypoints bias. We adopt PCA [3] to visualize the descriptors of the original images (a). When the description network is trained with SIFT (b), there are insufficiently trained areas (black boxes), which leads to false keypoints detection. On the contrary, when the description network is trained with grid-based random sample (c), all the areas in the image will be sufficiently trained.

Consequently, areas with few SIFT keypoints are usually under-optimized, as shown in Fig. 2. This bias limits the discriminativeness of the descriptors and leads to detection network produces considerable false keypoints detection. To address this problem, we use grid-based random sampling to generate query points. Specifically, we first split the image into \( N_g \) grids with the shape of \( g \times g \). Then we uniformly select \( N_g \) points with with one point in a grid. With this grid-based random sample strategy, the description network will be sufficiently trained in all areas, and thus detection network can produce more accurate keypoints.

3. Detection Network Training

In this section, we present more details on the detection network training.

As described in the main paper, we first extract the feature maps \( F_1 \) and \( F_2 \) from a image pair \( I_1 \) and \( I_2 \) with the frozen description network. Then we feed \( F_1 \) and \( F_2 \) into the detection network to produce the keypoint heatmaps, and model the keypoint distributions based on the heatmaps. Specifically, we divide these heatmaps into grids and select and model the keypoint distributions based on the heatmaps. The NMS size is set to be 3×3 due to the existence of low-resolution images, and the maximum keypoint numbers are limited to be 8192.

### 3.1 Detection Network Training

In this section, we present the hyper-parameters of our method on different datasets. During inference, we apply non-maximum suppression (NMS) to detect keypoints, and use a mutual nearest neighbour matcher for matching. Instead of resizing the images, we crop the images from the top-left side to guarantee both the height and width of the images are divisible by 16.

**HPatches Dataset [1]**. The NMS size is set to be 3×3 due to the existence of low-resolution images, and the maximum keypoint numbers are limited to be 8192.
Aachen Day-Night Dataset [10]. Because of the high image resolutions, the NMS size is set to be $7 \times 7$ on the Aachen Day-Night dataset, and the maximum keypoint numbers are limited to be $16k$. Note that, keypoints with scores smaller than 0.9 in the heatmaps are filtered out.

ETH Local Feature Benchmark [7]. The NMS size is set to be $7 \times 7$, and the maximum keypoints numbers are limited to be $20k$. Keypoints with scores smaller than 0.9 in the heatmaps are also filtered out. We additionally applying ratio test during matching with a threshold 0.8 to achieve robust reconstruction.
5. Limitations and Broader Impact

The PoSFeat suffers limited capability to deal with large rotation and scale changes. On the HPatches dataset, our PoSFeat produces limited performance on several scenes with pure rotation. On the ETH local feature benchmark, our PoSFeat cannot well handle the scenes with extreme scale changes thus has limited performance in #Imgs (e.g., only 419 images are registered in Madrid Metropolis).

The PoSFeat is a general local feature method, although we only apply it with image matching, visual localization and 3D reconstruction in our paper, it can be easily extended to recognize or reconstruct human faces. Therefore, the researches and the applications about the recognition or reconstruction of human faces must strictly respect the personality rights and privacy regulations.

6. Visualization

We present some qualitative results in this section. The image matching results on HPatches are shown in Fig. 3. The 3D models of Aachen are illustrated in Fig. 4, which is reconstructed with the features extracted by PoSFeat, and is used to do visual localization on Aachen Day-Night dataset. And the 3D reconstruction results on ETH local feature benchmark are shown in Fig. 5.

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