A REGION-BASED DESCRIPTOR NETWORK FOR UNIFORMLY SAMPLED KEYPOINTS

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ABSTRACT
Matching keypoint pairs of different images is a basic task of computer vision. Most methods require customized extremum point schemes to obtain the coordinates of feature points with high confidence, which often need complex algorithmic design or a network with higher training difficulty and also ignore the possibility that flat regions can be used as candidate regions of matching points. In this paper, we design a region-based descriptor by combining the context features of a deep network. The new descriptor can give a robust representation of a point even in flat regions. By the new descriptor, we can obtain more high confidence matching points without extremum operation. The experimental results show that our proposed method achieves a performance comparable to state-of-the-art.

Index Terms—keypoint extraction, feature descriptors, uniform sampling, deep learning

1. INTRODUCTION
Matching keypoint pairs between multiple images is an important problem to Structure-from-Motion (SfM) [1], Simultaneous Localization and Mapping (SLAM), camera pose estimation, image retrieval [2], 3D reconstruction [3]. The general process to get sparse matching keypoint pairs is to first detect the keypoints and then calculate their descriptors. Through some distance metric of the descriptors such as the Euclidean distance and some feature matching algorithm, such as the nearest neighbor search (NNS) algorithm [4], the keypoints can be matched.

For the hand-crafted method, the local feature extraction process is generally detect-then-describe. Firstly, detect the coordinates of the keypoints uses some custom extremum algorithm. And then according to some prior knowledge, a high-dimensional vector describing the features around the keypoint is designed. These keypoints are then matched by using these high-dimensional vectors. The best known traditional algorithm is SIFT [5], which obtains the position of the keypoints based on the extremum detection of the complicated Difference of Gaussian. It continues to be improved.

RootSIFT [6] enhances the matching accuracy through normalized descriptors. [7] uses binary descriptors to improve real-time performance. [8] proposes a quantization expression to provide sparse representation for image blocks. However, such algorithms usually only consider low-level information, such as corners [9] or blob-like structures [5, 10]. Their results deteriorate under some challenging conditions, e.g., the large variation of light intensity, sharp change of viewpoint, or weak texture area [11]. And in these challenging scenarios, they are easy to produce a lot of mismatched results, which increases the difficulty of further processing. Moreover, they often need to design a complex algorithm to complete the process of feature point detection and description.

Many learning-based approaches hope to obtain the coordinates or descriptors or both of them of the keypoints with a data-driven approach. MatchNet [12] is an early example. It uses a similarity measure network to calculate the similarity of descriptors, which significantly improves previous results. Later LIFT [13] is the first completely learning-based end-to-end network that outputs both keypoints coordinates and descriptors. DELF [14] is applied to the image retrieval task of street view markers, roughly locating the keypoints on the im-
age through an attention mechanism. SuperPoint [15] is based on the synthetic datasets, which also outputs keypoints coordinates and descriptors at the same time. D2-Net [16] obtains keypoints coordinates and descriptors by selecting soft local-max in a pre-trained network. These learning-based methods, which obtain the coordinates and descriptors at the same time, generally adopt multi-task optimization to train the network, which imperceptibly increases the training difficulty of the network. All of the above methods need some custom extremum to obtain the feature points of the texture region. Moreover, most of the methods focus on the local features of keypoints and do not consider the high-level information around the keypoints.

According to common sense, there is no key point in flat regions, like points C and D shown in Fig.1. For the points C and D with a small neighbor (red circles) neither give valid descriptions. With the increase of the receptive field, it is possible to find valid descriptions for points C and D with a larger neighbor (green circles). Therefore, we propose a descriptor extraction network that fuses more information which contains the features of the texture area in the green circle (fusion of the high-level information and low-level information around the keypoints), makes points C and D divisible, and ensures that points in the flat region can also be well matched.

Our contributions can be summarized from two aspects:

1. We introduce a simple uniform sampling method for keypoint extraction to enlarge the candidate range of keypoints, which can obtain a larger distribution of the matching feature point pairs accompanying by more abundant image information.

2. We propose a region-based descriptor network (RDN) that integrates high-level information and low-level information around the points, which has better expressive power and even makes the points in the flat region can be distinguished from each other.

2. PROPOSED METHOD

2.1. Motivation and Our Ideas

In general, the coordinates and the descriptors of the keypoints need to be obtained firstly for further matching. Most of the previous methods used various extremum points as feature points, which are concentrated in the region with rich texture. In this way, the points out of the rich texture regions are usually not considered as candidates of a matching point. We hope to integrate more comprehensive image information so that flat areas can also have feature points to participate in matching.
2.1.1. Keypoints Extraction

In many tasks, the keypoint does not have a unified definition, and whether it is an extreme point does not affect the result of matching, such as in the calculation of the fundamental matrix [17]. As long as a sufficient number of point pairs match correctly, we can calculate the relationship between the images, such as the rotation and translation of the image perspective. Therefore, we came up with a uniform sampling method on the image to extract keypoints.

2.1.2. Learning Descriptors

As shown in Fig.1, the local features extracted by the previous methods cannot well accomplish the matching of feature point pairs in flat regions, that is, the descriptors of feature points in flat regions are indistinguishable. So we propose a fusion of high-level information and low-level information convolutional neural network to address this problem.

2.2. Network Architecture

The proposed network, referred to as RDN, aims to generate valid descriptors for points of an input image even in flat regions. As shown in Fig.2, the input is an image \( I \in \mathbb{R}^{H \times W \times 3} \). The front part of the RDN is the feature extraction network (FEN) which is inspired by L2-Net [18] and R2D2 [19], and the latter part is a high-level feature fusion module (HFFM). The 128-dimensional vector generated by the FEN represents the low-level features \( (\text{d}_{\text{low}} \in \mathbb{R}^{H \times W \times 128}) \) around the keypoints. Then it serves as the input to the HFFM. The output of the HFFM is the high-level features \( (\text{d}_{\text{high}} \in \mathbb{R}^{H \times W \times 128}) \) around the keypoints. To effectively capture contextual relations around the keypoints, the HFFM starts with four fixed-size average pooling blocks for Spatial Pyramid Pooling (SPP): \( 64 \times 64, 32 \times 32, 16 \times 16 \), and \( 8 \times 8 \). Then the feature maps are upsampled to the same size as the input figure. By concatenating the outputs of the FEN \( (\text{d}_{\text{low}}) \) and the HFFM \( (\text{d}_{\text{high}}) \), we can obtain a 256-dimensional vector, for each pixel. To better compare the descriptors, an L2 normalization layer was added to normalize the descriptors. The final output are the dense descriptors \( \text{d}_{\text{output}} \in \mathbb{R}^{H \times W \times 256} \).

2.3. Training Loss

In terms of descriptor learning, the descriptors are expected to be distinctive and be avoiding mismatching. We adopt the triplet loss similar to D2-Net, which has been successfully applied in descriptors learning [20]. The RDN does not need to predict the coordinates of keypoints, so we remove the weighted part of loss calculation in D2-Net, and directly calculate the triplet loss between the distance of the descriptors of the matching keypoints and the descriptors of the mismatched keypoints. It can be formulated as follows:

\[
\text{Loss}(I_1, I_2) = \sum_{c \in C} f(p(c), n(c)),
\]

where \( I_1, I_2 \) are two images with the same scene, \( f \) indicates the triplet margin ranking loss, \( c \) denotes the correspondences, \( p \) represents the distance between the descriptors of the matched keypoints pair (correspondence), \( n \) is the nearest distance between the descriptors of the mismatched keypoints pair, \( C \) is the set of the correspondences in the two images. See [16] for more details.

3. EXPERIMENTS

3.1. Dataset and Implementation Details

To generate training data close to the real scenario, we use the MegaDepth Dataset [21] from the internet photo gallery. Since D2-Net has extracted the pixel-wise correspondences with the COLMAP [1][22], we directly use it as ground truth to train our network.

The architecture similar to L2-Net, pretrained on the Oxford and Pairs retrieval dataset [23] and the Aachen Day-Night dataset [24], was used to initializes the FEN. The HFFM was fine-tuned for 50 epochs using Adam with an initial learning rate \( 10^{-3} \), which was further divided by 2 every 10 epochs. 100 images were randomly selected from each scene for training to solve the problem of the unbalanced number of images in the scene. The size of the training batch is 1.

3.2. Qualitative and Visual Evaluation

To verify the effectiveness of our proposed method, we conduct some experiments on pictures taken with a mobile phone. As we can see in Fig.3, not only textured areas have many
matching points, but flat areas, such as tabletop, cabinet surface, and glass surface, can also get matching keypoints.

Our method is completed by referring to D2-Net, so we carry out some experiments comparing with D2-Net. D2-Net and our method are used to get the feature points and descriptors respectively in the experiment. The NNS algorithm is used to match the feature points, and then RANSAC is used to screen out the outliers. The final result is shown in Fig.4. We can see that D2-Net matches basically the points in the texture region, and our method has significantly more matching point pairs in the flat region than D2-Net. Our method can preserve more information about the image and introduce less error for subsequent advanced tasks.

### 3.3. Quantification and Camera Localization

Table 1. Results on the Aachen Day-Night dataset, we report the percentages of images that are successfully located under the 3 error thresholds. The best performance is shown in bold.

| Method     | 0.5m,2°   | 1m,5°    | 5m,10°   |
|------------|-----------|----------|----------|
| RootSIFT   | 33.7      | 52.0     | 65.3     |
| HAN+HN     | 37.8      | 54.1     | 75.5     |
| SuperPoint | 42.8      | 57.1     | 75.5     |
| DELF       | 39.8      | 61.2     | 85.7     |
| D2-Net     | 44.9      | 66.3     | **88.8** |
| R2D2       | 45.9      | 67.3     | **88.8** |
| RDN(ours)  | **65.3**  | **75.5** | **84.7** |

We evaluate our approach in a camera localization task. The dataset that we use is the Aachen Day-Night dataset with dramatic changes in illumination. This dataset has night-time images with unknown camera pose and day-time images with a known camera pose. The day-time images need to be reconstructed first to obtain the 3D scene structures, and then the night-time query images should be located from these 3D structures. We follow the evaluation protocol [24] and report the percentage of successful camera localization obtained from night-time image queries within three error threshold (0.5m,2°)/(1m,5°)/(5m,10°). The camera pose error consists of the camera position (meter) and the camera orientation (degree). We compare the performance of the proposed approach with other methods including RootSIFT, HardNet++ (HAN) with HesAffNet features (HN), SuperPoint, DELF, D2-Net, R2D2. In addition to our method, the data in Table 1 directly adopt the data of [19].

As we can see in Table 1, our approach achieves the best result under strict threshold conditions for camera pose estimation. By means of uniform sampling, our method retains more regional information, and meanwhile, by integrating more context information, obtains a more comprehensive description of point features and better express the information contained in the image. Therefore, our method can achieve the most accurate camera positioning. The reason why the effect is not good under the condition of a large error threshold is that the results obtained by our method in the reconstructed the 3D model and feature extraction of the night-time images mainly focus on the high-precision part, while the parts with low-precision are relatively few, so the influence of relaxing threshold is not as good as other methods. The results show that our simple approach can be used for estimating accurate camera pose.

### 4. CONCLUSIONS

In this paper, we introduce a new method to obtain keypoints without extremum operation, which significantly increases the range of keypoints acquisition. This may lead to a problem that points in a flat region have no locally meaningful features. To address this problem, we propose a region-based descriptor by combining the context features of a deep network. We obtain more expressive descriptors by combining high-level information and low-level information. Compared to our baseline D2-Net, we obviously obtain keypoints pairs of more regions that could express more information about the images. Moreover, our approach achieves the best performance in terms of camera positioning by collecting more information from the images under a strict threshold.
REFERENCES

[1] Johannes L Schönberger and Jan-Michael Frahm, “Structure-from-motion revisited,” in CVPR, 2016, pp. 4104–4113.

[2] James Philbin, Ondrej Chum, Michael Isard, Josef Sivic, and Andrew Zisserman, “Object retrieval with large vocabularies and fast spatial matching,” in CVPR, 2007, pp. 1–8.

[3] Jared Heinly, Johannes L Schönberger, Enrique Dunn, and Jan-Michael Frahm, “Reconstructing the world* in six days*(as captured by the yahoo 100 million image dataset),” in CVPR, 2015, pp. 3287–3295.

[4] Marius Muja and David G Lowe, “Scalable nearest neighbor algorithms for high dimensional data,” IEEE transactions on pattern analysis and machine intelligence, vol. 36, no. 11, pp. 2227–2240, 2014.

[5] David G Lowe, “Distinctive image features from scale-invariant keypoints,” International journal of computer vision, vol. 60, no. 2, pp. 91–110, 2004.

[6] Relja Arandjelović and Andrew Zisserman, “Three things everyone should know to improve object retrieval,” in CVPR, 2012, pp. 2911–2918.

[7] Vassileios Balntas, Lilian Tang, and Krystian Mikolajczyk, “Bold-binary online learned descriptor for efficient image matching,” in CVPR, 2013, pp. 2842–2849.

[8] Xavier Boix, Michael Gygli, Gemma Roig, and Luc Van Gool, “Sparse quantization for patch description,” in CVPR, 2013, pp. 10–5244.

[9] Christopher G Harris, Mike Stephens, et al., “A combined corner and edge detector,” in Alvey vision conference, 1988, vol. 15, pp. 63–86, 2004.

[10] Krystian Mikolajczyk and Cordelia Schmid, “Scale & affine invariant interest point detectors,” International journal of computer vision, vol. 60, no. 1, pp. 63–86, 2004.

[11] Hajime Taira, Masatoshi Okutomi, Torsten Sattler, Mircea Cimpoi, Marc Pollefeys, Josef Sivic, Tomas Pajdla, and Akihiko Torii, “Inloc: Indoor visual localization with dense matching and view synthesis,” in CVPR, 2018, pp. 7199–7209.

[12] Xufeng Han, Thomas Leung, Yangqing Jia, Rahul Sukthankar, and Alexander C Berg, “MatchNet: Unifying feature and metric learning for patch-based matching,” in CVPR, 2015, pp. 3279–3286.

[13] Kwang Moo Yi, Eduard Trulls, Vincent Lepetit, and Pascal Fua, “LIFT: Learned invariant feature transform,” in ECCV, 2016, pp. 467–483.

[14] Hyeonwoo Noh, Andre Araujo, Jack Sim, Tobias Weyand, and Bohyung Han, “Large-scale image retrieval with attentive deep local features,” in ICCV, 2017, pp. 3456–3465.

[15] Daniel DeTone, Tomasz Malisiewicz, and Andrew Rabinovich, “SuperPoint: Self-supervised interest point detection and description,” in CVPRW, 2018, pp. 224–236.

[16] Mihai Dusmanu, Ignacio Rocco, Tomas Pajdla, Marc Pollefeys, Josef Sivic, Akihiko Torii, and Torsten Sattler, “D2-Net: A trainable CNN for joint detection and description of local features,” arXiv preprint arXiv:1905.03561, 2019.

[17] Yinqiang Zheng, Shigeki Sugimoto, and Masatoshi Okutomi, “A practical rank-constrained eight-point algorithm for fundamental matrix estimation,” in CVPR, 2013, pp. 1546–1553.

[18] Yurun Tian, Bin Fan, and Fuchao Wu, “L2-Net: Deep learning of discriminative patch descriptor in euclidean space,” in CVPR, 2017, pp. 661–669.

[19] Jerome Revaud, Cesar De Souza, Martin Humenberger, and Philippe Weinzaepfel, “R2d2: Reliable and repeatable detector and descriptor,” in NeurIPS, 2019, pp. 12405–12415.

[20] Anastasiia Mishchuk, Dmytro Mishkin, Filip Radenovic, and Jiri Matas, “Working hard to know your neighbor’s margins: Local descriptor learning loss,” in NeurIPS, 2017, pp. 4826–4837.

[21] Zhengqi Li and Noah Snavely, “Megadepth: Learning single-view depth prediction from internet photos,” in CVPR, 2018, pp. 2041–2050.

[22] Johannes L Schönberger, Enliang Zheng, Jan-Michael Frahm, and Marc Pollefeys, “Pixelwise view selection for unstructured multi-view stereo,” in ECCV, 2016, pp. 501–518.

[23] Filip Radenović, Ahmet Iscen, Giorgos Tolias, Yannis Avrithis, and Ondřej Chum, “Revisiting oxford and paris: Large-scale image retrieval benchmarking,” in CVPR, 2018, pp. 5706–5715.

[24] Torsten Sattler, Will Maddern, Carl Toft, Akihiko Torii, Lars Hammarstrand, Erik Stenborg, Daniel Safari, Masatoshi Okutomi, Marc Pollefeys, Josef Sivic, et al., “Benchmarking 6dof outdoor visual localization in changing conditions,” in CVPR, 2018, pp. 8601–8610.