A Detector-oblivious Multi-arm Network for Keypoint Matching
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Abstract—This paper presents a matching network to establish point correspondence between images. We propose a Multi-Arm Network (MAN) capable of learning region overlap and depth, which can greatly improve keypoint matching robustness while bringing an extra 50% of computational time during the inference stage. By adopting a different design from the state-of-the-art learning based pipeline SuperGlue framework, which requires retraining when a different keypoint detector is adopted, our network can directly work with different keypoint detectors without time-consuming retraining processes. Comprehensive experiments conducted on four public benchmarks involving both outdoor and indoor scenarios demonstrate that our proposed MAN outperforms state-of-the-art methods.

Index Terms—Keypoint matching, Image matching, Pose estimation, Visual localization

I. INTRODUCTION

Finding keypoint correspondences is a fundamental computer vision problem. Keypoint correspondences are often solved through matching local features under certain geometric constraints (e.g., mutual nearest and ratio tests). Matching algorithms calculate similarities between the keypoint of an image and all keypoints on another image.

In this work, we expect the matching network to be aware of region-level information after communicating cross images. We propose keypoint matching combined with solving two auxiliary tasks, through which regional-level correspondence can be estimated. Specifically, when the network estimates a feature for each keypoint, we expect that this feature could contain an overlap region and depth region information related to the keypoint. Fig. 1 shows the reliable correspondences produced by our method and designed using the abovementioned idea, showing that this method is more effective than a current state-of-the-art matching approach (SuperGlue [1]).

SuperGlue [1] demonstrates remarkable performance in both outdoor and indoor datasets for keypoint matching, however, it requires keypoint coordinates, descriptions, and confidence; hence it needs to be retrained each time it adapts to different keypoint detectors. This training process requires a half month or more, even when using the latest graphics cards (V100). After conducting experiments on the influence of three keypoint attributes to SuperGlue, we find that keypoint confidence has little effect on performance (see Table I). This discovery provides experimental support for removing keypoint confidence; this is an important step for proposing detector-oblivious networks.

We introduce a new design into the matching pipeline, the detector-oblivious description network, which uses keypoint coordinates from any detectors as inputs and outputs unique keypoint descriptions. This design entails that our pipeline does not need to be retrained when a new detector is adopted.

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TABLE I

| p   | d   | c   | MegaDepth @5° | @10° | @20° |
|-----|-----|-----|---------------|------|------|
| SP  | SP  | SP  | 39.90         | 52.49| 63.07|
| SP  | SP  | RAND| 40.18         | 52.64| 63.21|
| SP  | SP  | ZERO| 36.96         | 49.88| 60.59|
| SP  | SP  | ONE | 38.70         | 51.59| 62.74|

Fig. 1. When images under drastic viewpoint and scale changes, the state-of-the-art pipeline SuperGlue [1] fails to produce reliable matching. However our MAN can more effectively find the correspondences. One example is illustrated here, where red and green lines indicate incorrect and correct matches, respectively.
In summary, our contributions are threefold:

- We propose a Multi-Arm Network (MAN) for keypoint matching, which utilizes regional-level correspondence (overlap and depth) to enhance the robustness of keypoint matching.
- We develop a detector-oblivious description network ensuring that the matching pipeline is able to adapt to any keypoint detector without the requirements of a time-consuming retraining procedure.
- Comprehensive experiments using four public benchmarks demonstrate that our pipeline facilitates state-of-the-art results on both outdoor and indoor datasets.

II. RELATED WORK

Keypoints on images are usually described in terms of their local features. Generally, we estimate geometric transformations between images by matching local features. This matching process can be conducted using learned networks.

A. Matching keypoints using local features

Matching keypoints using local features typically consists of a nearest neighbor search coupled with additional constraints. These constraints can include the mutual nearest neighbor, ratio tests [2], and heuristics (e.g., neighborhood consensus [3]). Deep learning studies generally tend to obtain better and more distinctive keypoint descriptors. L2Net [4] proposes learning discriminative descriptors in Euclidean space. HardNet [5] introduces a loss function for learning local feature descriptors inspired by Lowe’s matching criterion for SIFT [2]. He et al. [6] improved the learning of local features by directly optimizing a ranking-based retrieval performance metric, termed Average Precision. LF-Net [7] presents a deep architecture and training strategy by which a local feature pipeline can be determined from scratch. RF-Net [8] proposes an end-to-end trainable matching network based on the receptive field. SOSNet [9] incorporates Second Order Similarity Regularization for learning local feature descriptors. Ebel et al. [10] proposed that the support region of local features may be determined by directly using a log-polar sampling scheme. HyNet. [11] introduced a hybrid similarity measure for triplet margin loss, a regularization term constraining the normalization of the descriptor, and a new network architecture capable of performing L2 normalization of all intermediate feature maps and their output descriptors. Wang et al. [12] proposed a weakly-supervised framework capable of learning feature descriptors solely from relative camera poses between images. Shen et al. [13] explored a scale awareness learning approach for finding pixel-level correspondences based on the intuition that keypoints need to be extracted and described on appropriate scales.

B. Matching keypoints using learned networks

Matching keypoints using local features still find correspondences by nearest neighbor searches, discards the feature geometric information and ignores assignment structures. SuperGlue [1] proposes learning this information for matching. It firstly merges keypoints coordinates, descriptions, and confidence by a hierarchical Transformer [14], then uses the Sinkhorn algorithm [15], [16] to approximately solve the optimal transport problem [17]. Because keypoint detectors are trained under different loss functions and designed by different algorithms, they generally give different descriptions (and confidence) to the same keypoint coordinate. Therefore, it is necessary to retrain SuperGlue [1] each time it is combined with different keypoint detectors, because the estimated match relies on keypoints attribution. Nevertheless, it is possible to use this matching network using the approach presented in the Method section.

C. Learning with auxiliary tasks

Learning with auxiliary tasks to enhance the performance of the primary task is not a new concept for deep learning. However, auxiliary tasks cannot be borrowed directly from other networks without some consideration. Rich [18] noted that if auxiliary tasks are unrelated to the primary task, the learned features in their shared weights can be contaminated by outlier training signals from the unrelated auxiliary tasks; this can result in performance degradation of the primary task. Therefore, it is necessary to find auxiliary tasks having mutually beneficial relationships with the primary task. Mordan et al. [19] developed a means of estimating the depth and normal to enhance the precision of object detection. Zhou et al. [20] enhanced the pose estimation from depth prediction. In this work, we estimate overlap and depth regions in order to enhance the keypoint matching.

III. METHOD

In this section, we introduce our detector-oblivious MAN for keypoint matching. Sec. III-A presents the formulation of the problem of keypoint matching. Sec. III-B introduces the approach by which the detector-oblivious network is built. Sec. III-C introduces the auxiliary tasks and loss functions developed in the MAN for overlap and depth region estimation.

A. Problem formulation

We consider a pair of images $A$ and $B$, each with a set of keypoint coordinates $p$, which consist of $x$ and $y$ coordinates, $p_i := (x, y)$. Images $A$ and $B$ have $M$ and $N$ keypoint coordinates, indexed by $A := \{1, \ldots, M\}$ and $B := \{1, \ldots, N\}$, respectively. Our objective is to train a network capable of outputting a similarity matrix $M \in [0, 1]^{M \times N}$ from two sets of keypoint coordinates.

B. Detector-oblivious approach

As illustrated in Fig. 3 SuperGlue requires input with keypoint descriptions $d$, coordinates $p$, and confidence $c$, which are represented as local features. Descriptions $d_i \in \mathbb{R}^D$ and confidence $c \in [0, 1]$ can be extracted using a network, e.g., SuperPoint [21] and R2D2 [22], or an algorithm, e.g., SIFT [2].

According to the results of our experiments in Table II training SuperGlue under SuperPoint [21], followed by integration with other detectors, e.g., R2D2 [22], results in poor
Because SuperPoint and R2D2 are trained under different network architectures and loss functions, they will result in two completely different keypoint descriptions. If a network can fuse regional information into features, we use two auxiliary networks to estimate the overlap and depth regions. In contrast with SuperGlue, which estimates only one similarity matrix to perceive correspondences at the region level (e.g., the overlap and depth regions). The concept of the correspondence region depends both on images A and B, rather than just a single image. Therefore, descriptors extracted from either image are insufficient to infer relationships between the regions. The keypoint descriptors \( d_A \) and \( d_B \) are required to communicate with each other for region estimation. We borrowed the cross-attention module proposed by SuperGlue \cite{Saragih_2018_CVPR} to communicate region-level information between images. When the network fuses regional information into features, we use two auxiliary networks to estimate the overlap and depth regions. In contrast with SuperGlue, which estimates only one similarity matrix to predict the matching result, our MAN grows three feature arms \((\tilde{f}, \alpha, \beta)\) in Fig. 2) to estimate three similarity matrices. For inference, we keep only the matching results that survive in all three similarity matrices, thereby increasing the reliability of the matching (see Fig. 4).

**Overlap Region Estimation Task**: As shown in Fig. 2, our detector-oblivious network is fed with the keypoint coordinates \( p \) and outputs the keypoint features \( d \). We use the cross-attention module to produce matching features \( f \), then we use a Multilayer Perceptron (MLP) to transform \( f \) to a new high-dimensional space, represented as \( \tilde{f} \), which may be treated as new representations for the keypoint. Before conducting the matching process, we expect that features \( \tilde{f} \) contain the information needed to determine whether their keypoints fall into the overlap area. To this end, we propose the Overlap Estimation (OVE) Loss \( L_{\text{OVE}} \) to train the auxiliary network \( \phi \) : 

\[
\begin{align*}
\upsilon_i^A = & \phi \left( \tilde{f}_i^A \right) = \text{Sigmoid} \left( \text{MLP} \left( \tilde{f}_i^A \right) \right), \\
L_{\text{OVE}}^A = & L_{\text{cross-entropy}} \left( y_i^A, \upsilon_i^A \right), \\
L_{\text{OVE}} = & L_{\text{OVE}}^A + L_{\text{OVE}}^B,
\end{align*}
\]

**C. The multi-arm network**

Existing matching methods find correspondences directly at the pixel level. Here, we attempt to enable the network to perceive correspondences at the region level (e.g., the overlap and depth regions). The concept of the correspondence region depends both on images A and B, rather than just a single image. Therefore, descriptors extracted from either image are insufficient to infer relationships between the regions. The keypoint descriptors \( d_A \) and \( d_B \) are required to communicate with each other for region estimation. We borrowed the cross-attention module proposed by SuperGlue \cite{Saragih_2018_CVPR} to communicate region-level information between images. When the network fuses regional information into features, we use two auxiliary networks to estimate the overlap and depth regions. In contrast with SuperGlue, which estimates only one similarity matrix to predict the matching result, our MAN grows three feature arms \((\tilde{f}, \alpha, \beta)\) in Fig. 2) to estimate three similarity matrices. For inference, we keep only the matching results that survive in all three similarity matrices, thereby increasing the reliability of the matching (see Fig. 4).
where \( y^A_i \in (0, 1) \), and \( y^B_i \in \{0, 1\} \) is the binary label.

**Depth Region Estimation Task:** The overlap region estimation task is required to train features \( f \) to predict whether their keypoints fall into the overlap area. The depth region estimation task trains features \((\alpha, \beta)\) in order to predict into which depth region of images \( A \) and \( B \) it falls. We use Otsu’s method \( [23] \) to split the image into close-scene and far-scene regions according to image depth. Hence, the depth region estimation auxiliary network \( \psi \) also performs a binary classification.

Fig. 4 shows the data for training network \( \psi \) given a pair of images \((A, B)\) and their corresponding depth maps \((D^A, D^B)\). We divide images into \( C = 3 \) regions according to depth values, of which the valid regions occupy two regions (blue and yellow) and the invalid region occupies one (black), as follows

\[
\epsilon = \text{OTSU}(D) 
\]

\[
\epsilon = \begin{cases} 
0 & \text{if } D_{ij} \in [D^\text{min}, \epsilon), \\
1 & \text{if } D_{ij} \in [\epsilon, D^\text{max}], \\
2 & \text{if } D_{ij} \text{ is invalid}, 
\end{cases} 
\]

where \( D \) represents the depth map of an image, \( D^\text{min} \) and \( D^\text{max} \) represent the minimum and maximum values of a depth map, and \( \epsilon \) represents the region class.

As illustrated in Fig. 2, our detector-oblivious network estimates a feature \( f^A \) to describe a keypoint on the coordinate \( p^A \) in image \( A \). Then, two MLPs are used to obtain features \( \alpha^A \) and \( \beta^A \). For these two features, we anticipate the following:

- \( \alpha^A \) can be used to estimate which region of image \( A \) the keypoint \( p^A \) falls in,
- \( \beta^A \) can be used to estimate which region of image \( B \) the keypoint \( p^A \)’s corresponding point falls in.

To this end, we propose the DEPth region Estimation (DEE) Loss \( \mathcal{L}^A_{\text{DEE}} \) as follows to train the auxiliary network \( \psi^A : \)

\[
\hat{\eta}^A_i = \psi^A (\alpha^A_i) = \text{Sigmoid} \left( \text{MLP} \left( \alpha^A_i \right) \right), 
\]

\[
\mathcal{L}^A_{\text{DEE}} = \mathcal{L}_{\text{cross-entropy}} \left( \hat{g}^A_i, \hat{\eta}^A_i \right), 
\]

where \( \hat{\eta}^A_i \in (0, 1) \), and \( \hat{g}^A_i \in \{0, 1\} \) are the binary labels. Similarly, we obtain Loss \( \mathcal{L}^B_{\text{DEE}} \) from \( \beta^A \) to train network \( \psi^B \).

For features that estimate regions in the same target image, we expect the following:

- \( \alpha^A \) to match \( \alpha^B \) (their target regions are on image \( A \)),
- \( \beta^A \) to match \( \beta^B \) (their target regions are on image \( B \)).

In summary, the final loss function \( \mathcal{L}_{\text{DEE}} \) for the depth region estimation task can be formulated as follows:

\[
\mathcal{L}_{\text{DEE}} = \mathcal{L}^A_{\text{DEE}} + \mathcal{L}^B_{\text{DEE}} + \mathcal{L}^A_{\text{Match}} + \mathcal{L}^B_{\text{Match}}. 
\]

where the Match Loss \( \mathcal{L}_{\text{Match}} \) is proposed by SuperGlue and minimizes the negative log-likelihood of the similarity matrix \( M \).

For inference, the auxiliary networks \((\psi, \phi)\) can be detached, while its features \((f, \alpha, \beta)\) grow on the three arms are reserved. We infer the matching results from three similarity matrices and keep the matching results that survive in all three similarity matrices.

**IV. Experiments for the Detector-oblivious Approach**

In this section, we test the influence of keypoint coordinates \( p \), descriptions \( \phi \), and confidence \( c \) for keypoint matching using SuperGlue \( [7] \) in outdoor and indoor scenes.

**Metrics:** Following previous work SuperGlue \( [7] \) to report the area under the cumulative error curve (AUC) of the pose error at certain thresholds \((5^\circ, 10^\circ, \text{and} 20^\circ)\). The pose error is the maximum of the angular errors in rotation and translation. Poses are computed by estimating the essential matrix with OpenCV’s findEssentialMat and RANSAC \([24, 25]\) using an inlier threshold of one pixel divided by the focal length, followed by recoverPose. In addition, we also report the

\[1\] For better understanding, we color symbols in red and blue for the operations whose target images are images \( A \) and \( B \).
MegaDepth consists of MegaDepth [27] and YFCC100M datasets [28] for testing.

A. Outdoor scenarios

The SuperGlue model used in this experiment changed the generalization of SuperGlue integrated with different detectors, perPoint (SP) and recorded as #1 in Table I. To test the generalization of SuperGlue, we changed the keypoints from SP to R2D2, random numbers, zeros, and ones, as shown in Table II, after changing keypoint confidence from SP to R2D2, random numbers, zeros, and ones, as shown in records #4 - #7, in two datasets, the performance variance is small. In addition, we obtained the best pose estimation result for MegaDepth when setting the keypoint confidence randomly, rather than using the original SP.

Implement details: The SuperGlue model used in this experiment is the official release model, which requires inputs in the form of keypoint coordinates (2-dim), descriptors (256-dim), and confidence (scalar). To fit the description input dimension of 256, we trained a 256-dim R2D2 [22] by its official release code (the original R2D2 output 128-dim descriptors for the keypoints).

B. Indoor scenarios

Datasets: For the indoor scenario, we used the ScanNet [32] and the SUN3D [33] datasets. ScanNet is a large-scale indoor dataset composed of monocular sequences with ground-truth poses and depth images. We selected 1500 image pairs from these well-defined test sequences for evaluation, which is similar to the test data used in SuperGlue. The SUN3D dataset comprises a series of indoor videos captured using a Kinect, with 3D reconstructions; we used 14872 image pairs from the well-defined test sequences for evaluation. For testing, images were resized such that their longest dimensions are equal to 640 pixels. We detected 1024 keypoints for both R2D2 and SP.

Results: As shown in Table II, changing the keypoint coordinates p as shown in record #2, the performance of pose estimation is decreased by more than 18% relative to MegaDepth. In YFCC, although this phenomenon is alleviated, the performance is still degraded. After changing the keypoint descriptors d as shown in record #3, the model did not work for either datasets. Because SuperGlue is only trained under the SP description, it cannot adapt to R2D2. After replacing keypoint confidence c from SP to R2D2, random numbers, zeros, and ones, as shown in records #4 - #7, in two datasets, the performance variance is small. In addition, we obtained the best pose estimation result for MegaDepth when setting the keypoint confidence randomly, rather than using the original SP.

### Table II: Influence of Keypoint Coordinates, Descriptions, and Confidence for Outdoor and Indoor Pose Estimation. The First Column Represents the Number of the Experiment.

| # Outdoor | p   | d   | c   | MegaDepth   | YFCC   |
|-----------|-----|-----|-----|-------------|--------|
|           |     |     |     | @5° @10° @20° P | @5° @10° @20° P |
| 1         | SP  | SP  | SP  | 39.90 52.49 63.07 | 92.88 25.91 |
| 2         | R2D2 | SP | SP  | 20.90 30.98 40.82 | 87.09 28.21 |
| 3         | SP  | R2D2 | SP  | 0.00 0.14 0.45 1.01 0.52 | 0.00 0.00 0.00 0.11 0.03 |
| 4         | SP  | SP  | R2D2 | 37.02 49.68 60.30 92.35 22.89 | 38.83 59.43 75.78 98.51 23.28 |
| 5         | SP  | SP  | RAND | 40.18 52.64 63.21 | 92.76 25.95 |
| 6         | SP  | SP  | ZERO | 36.96 49.88 60.59 91.05 25.95 | 37.86 58.27 75.00 98.48 24.07 |
| 7         | SP  | SP  | ONE  | 38.70 51.59 62.74 92.81 26.49 | 38.60 58.91 75.46 98.42 24.44 |

| # Indoor  | p   | d   | c   | ScanNet     | SUN3D    |
|-----------|-----|-----|-----|-------------|----------|
|           |     |     |     | @5° @10° @20° P | @5° @10° @20° P |
| 1         | SP  | SP  | SP  | 16.45 33.62 51.96 | 84.13 31.68 |
| 2         | R2D2 | SP | SP  | 4.66 12.81 24.00 68.53 16.33 | 3.87 11.13 23.74 83.23 34.37 |
| 3         | SP  | R2D2 | SP  | 0.00 0.00 0.00 0.60 0.01 | 0.00 0.00 0.02 0.83 0.02 |
| 4         | SP  | SP  | R2D2 | 16.04 33.35 51.69 83.83 31.87 | 7.07 17.96 33.86 86.94 45.04 |
| 5         | SP  | SP  | RAND | 15.54 32.77 50.47 83.31 31.78 | 7.17 18.24 34.10 86.78 45.20 |
| 6         | SP  | SP  | ZERO | 15.23 31.33 49.23 84.07 31.41 | 6.89 17.54 33.31 87.11 44.76 |
| 7         | SP  | SP  | ONE  | 14.70 31.70 49.34 82.58 31.61 | 7.07 18.14 33.94 86.32 45.09 |
randomly, while in the ScanNet, the original still exhibits the best performance.

### C. Keypoint confidence in matching

Based on the experiment results obtained herein, we conclude that the p and d dominate the matching performance of SuperGlue. With regards to c, we cannot say that c is insignificant for matching; however, currently, in the SuperGlue architecture, it does not make a significant contribution to matching. In order to save time in processing confidence, the confidence score can be omitted.

It is intuitive that the confidence of the keypoints is initially used for keypoint selection. In the matching stage, the keypoints are selected, all of which are treated equally for the matching method or network; therefore, the keypoint confidence is not important.

However, situations may arise in which SuperGlue does not use the information in c appropriately. In these cases, a better approach could be designed to extract valuable information from c by combining the confidence value with the final matching results for a joint consideration and calculation. In this work, we chose to remove c when matching keypoints in order to achieve the purpose of detector-oblivious processing.

### V. EXPERIMENTS FOR THE MULTI-ARM NETWORK

This section compares our MAN against state-of-the-art techniques in relative pose estimation and visual localization tasks. We trained the indoor model on the ScanNet [32] dataset and the outdoor model on the MegaDepth [27] following the details provided by SuperGlue [1]. In details, the keypoint detector we used in training is the SuperPoint [21].

#### A. Relative pose estimation

**Baselines:** Following SuperGlue [1], we compare our multi-arm detector-oblivious network against state-of-the-art matchers applied to SIFT and SuperPoint features – the Nearest Neighbor (NN) matcher and various outlier rejectors: the mutual NN constraint, PointCN [34], OANet [35] and ACNe [36]. For all methods considered, we report the results using their official codes or models.

**Outdoor scenario:** As shown in Table III both MegaDepth and YFCC, our approach outperforms all baselines at all relative pose thresholds and the matching precision, when applied to both SuperPoint and SIFT. Compare with SuperGlue, after training with two auxiliary tasks; our multi-arm detector-oblivious network shows steady improvement.

**Indoor scenario:** As shown in Table III our approach achieves the best pose estimation and matching precision in the two datasets when integrating with both SuperPoint and SIFT.
Compared with SuperGlue, after adding the two auxiliary tasks, both the pose estimation and the matching precision are improved. SuperGlue obtains better matching scores indicating that it finds more correspondences under the same keypoints. Our method tends to find more reliable correspondences with auxiliary constraints, thereby reducing the number of matches and resulting in lower matching scores than SuperGlue.

**Comparison with Detector-free methods:** We also compared our method against recent detector-free methods [37], [38], which aim to find correspondences without using a keypoint detector. This is considered an intermediate solution between sparse-matching and dense-matching and can be called “semi-dense matching.”

In terms of results, our method performs better than DFM [37], likely because the transformation between the test image pairs is more complex than the homography transformation predicted by DFM in its first stage, so DFM does not achieve its best results. If DFM can predict more complex transformations in its first stage, it should achieve better results.

LoFTR [38] achieves better results than our method, potentially due to its coarse-to-fine architecture. In the coarse-level stage, LoFTR gets more dense coarse correspondences compared to detector-based methods and then refines them in the fine-level stage to obtain a better pose estimate.

**B. Visual localization**

**Datasets:** The Aachen Day-Night dataset [39], [40] evaluates local feature matching for day-night localization. For each of the 98 night-time images contained in the dataset, up to 20 relevant day-time images with known camera poses are given. Following SuperGlue [1], we extracted up to 4096 keypoints per image with SuperPoint, matched them with MAN, triangulated an SfM model from posed day-time database images, and register night-time query images with the image matches and COLMAP [29].

**Metrics:** Following SuperGlue [1], we used the code and evaluation protocol from [40] and report the percentage of night-time queries localized within given error bounds on the estimated camera position and orientation. In detail, the Aachen Day-Night benchmark measures the percentage of query images localized within $X$ m and $Y$ ° of their ground truth pose. This benchmark defines three pose accuracy intervals by varying the thresholds: *High-precision* (0.5m, 2°), *medium-precision* (1m, 5°), and *coarse-precision* (5m, 10°).

**Baselines:** Following SuperGlue [1], we compare our method against SuperPoint [21], D2-Net [41], R2D2 [22], UR2KID [42] and SuperGlue [1].

**Results:** As reported in Table IV when compared with SuperGlue [1], our method achieves a better result than it under the 0.5m/2° threshold and achieves comparable results under the 1m/5° and 5m/10° thresholds. We conjecture that the multi-arm architecture we propose can improve the performance of the network at high-precision (0.5m/2°), but not at medium-precision (1m/5°). Compared with other methods, our method performs similarly or better despite using significantly fewer keypoints. In general, our method generalizes well in visual localization.

**VI. ABLATION STUDY**

As shown in Table V we trained eight models for quantitative comparison. Model #4 is the finalized one, which compares other baseline methods in experiments. We tested these eight models in both outdoor and indoor scenarios in order to evaluate our design decisions.

Comparing models #1 and #2 shows that the overlap estimation task proposed herein can improve the matching precision and leads to estimate more accurate poses between images. Model #3 is trained using two auxiliary tasks with Single-Arm architecture. We showed experimentally that allowing one feature to simultaneously learn the two auxiliary tasks will lead to performance degradation, however, adding the Multi-Arm architecture and allowing multiple features to learn different auxiliary tasks improves the performance as shown in #4. If only the Multi-Arm architecture is used and multiple features are not trained with auxiliary tasks, the performance will decline slightly as shown in model #5.

In the depth estimation auxiliary task, we found that allowing the network to estimate two depth regions (close-scene and far-scene regions) improves the matching results as shown in model #6. We also attempted to allow the network to predict three and four regions in the auxiliary task; this resulted in a degradation of the performance as shown in models #7 and #8. We propose that this is because too complex auxiliary tasks affect the learning of the primary task.

When designing auxiliary networks, it is important to ensure that they play an auxiliary role and we expect their optimization to work toward the main matching task, not only auxiliary tasks. Therefore, we used only three layers of MLP to design the auxiliary network. It is difficult for such a lightweight auxiliary network to learn complex capabilities, such as accurately estimating the overlap area or depth region in which the keypoints fall. However, we think that it is interesting to find the keypoints in the overlap area first or predict the depth region of the keypoints accurately. If the network can exclude keypoints outside the overlap area, we could eliminate many potential mismatches in advance. If the network can estimate the keypoint depth region precisely, we could only match the corresponding area’s keypoints, which could also prevent matches in the non-corresponding regions.
The experiment results demonstrate our method does not need to be retrained when a new detector is adopted in testing.

VII. CONCLUSIONS

This work proposes a multi-arm network to extract information from overlap and depth regions in images, which provides extra supervision signals for training. Solving the auxiliary tasks of OVerlap Estimation (OVE) and DEpth region Estimation (DEE) help significantly improve the keypoint matching performance while bringing the little computational cost in inference. Besides, we designed a detector-oblivious description network and integrated it into the matching pipeline. This design makes our network can directly adapt to unlimited key-point detectors without a time-consuming retraining process.

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Indoor

Outdoor

SuperPoint+SuperGlue

SuperPoint+MAN

Fig. 5. Qualitative image matches. We compared MAN and SuperGlue [1] in indoor and outdoor environments. Red and green lines indicate incorrect and correct matches, respectively.

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