1. Implementation Details

1.1. Architecture of Co-visible Area Segmentation Module

In order to obtain the co-visible area probability map, we borrowed the structure of DETR [3] and used a query to perform regression on the feature map. The specific network architecture is shown in the Fig 1. Firstly, the spatial attention map $F_{i\text{attn}} \in \mathbb{R}^{1 \times h \times w}$ by the dot product operation of $Q \in \mathbb{R}^{1 \times 1 \times C}$ and $F_{i\text{2/8}} \in \mathbb{R}^{C \times h \times w}$, and then perform element-wise multiplication of $F_{i\text{attn}}$ and $F_{i\text{2/8}}$, followed by a shortcut connection to obtain $F_{i\text{co}} \in \mathbb{R}^{C \times h \times w}$. Finally, a simple block with two convolution layers are used to obtain the co-visible area probability map, where the first convolution is followed by a ReLU activation and the second convolution is followed by a Sigmoid function.

2. More Experiments

2.1. Additional Evaluation Metrics for HPatches

Metrics. Since the homography estimation accuracy contains the effect of the OpenCV-RANSAC, we use Mean Matching Accuracy (MMA) on the Hpatches [1] dataset to evaluate different methods. We use the ratio of correctly matched features within thresholds of 1, 2, and 3 pixels, respectively, and the maximum amount of matches is limited to 1024. Results in Tab.1 show that Adamatcher outperforms other methods in terms of matching accuracy. Since adaptive assignment eliminates the ambiguity of matching in supervision and inference, AdaMatcher is able to generate more accurate matches when the viewing angle changes.

2.2. Results on YFCC100M

The YFCC100M [15] dataset is also used to conduct experiments to compare AdaMatcher with several baseline
## 2.3. Indoor Pose Estimation

To validate the generalizability of different detector-free methods, we perform indoor pose estimation experiments on the ScanNet [5] dataset using models trained on the MegaDepth [8] dataset. We use the test split with 1500 image pairs following the experimental setting of [4, 12, 13]. To align with the existing methods [4, 13, 14], we resized all test images to $480 \times 640$. We use the same evaluation protocols as in Sec. 2.2. As presented in Tab.3, AdaMatcher has a significant performance improvement on different baselines [4, 13, 14].

## 2.4. Computational Costs of Feature Interaction

We evaluate the computation and parameters between LoFTR’s feature interaction module [13] and our CFI module (using linear attention [7] as in LoFTR). The size of input tensor is $60 \times 80 \times 256$. As shown in Tab.4, compared to LoFTR’s feature interaction module (consisting of four sets of self- and cross-attention layers), our CFI module reduces about 38.79% of the computational costs and 14.29% of the parameters.

| Method          | Flops(G) | Param(MB) |
|-----------------|----------|-----------|
| LoFTR module    | 51.82    | 5.25      |
| CFI             | 31.74    | 4.50      |

Table 4. Computational complexity of feature interaction module

Figure 2. Qualitative image matches on Hpatches dataset. Matches with projection error less than the threshold are displayed in green, otherwise they are displayed in red.
3. D. Qualitative Results

We present more qualitative comparisons of AdaMatcher and baselines on Hpatches [1] dataset and MegaDepth [8] dataset. In Fig.2, we display inlier and outlier matches using different projection thresholds to compare the matching accuracy of different methods on the Hpatches dataset. Fig.3 presents more qualitative results on the MegaDepth [8] dataset and Fig.4 shows more qualitative results of the co-visible area estimation.
Figure 3. Qualitative image matches on MegaDepth dataset. Green indicates that epipolar error in normalized image coordinates is less than $1 \times 10^{-4}$, while red indicates that it is exceeded.
Figure 4. Qualitative co-visible area segmentation
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