Abstract

Finding correspondences across images is an important task in many visual applications. Recent state-of-the-art methods focus on end-to-end learning-based architectures designed in a coarse-to-fine manner. They use a very deep CNN or multi-block Transformer to learn robust representation, which requires high computation power. Moreover, these methods learn features without reasoning about objects, shapes inside images, thus lacks of interpretability. In this paper, we propose an architecture for image matching which is efficient, robust, and interpretable. More specifically, we introduce a novel feature matching module called TopicFM which can roughly organize same spatial structure across images into a topic and then augment the features inside each topic for accurate matching. To infer topics, we first learn global embedding of topics and then use a latent-variable model to detect-then-assign the image structures into topics. Our method can only perform matching in co-visibility regions to reduce computations. Extensive experiments in both outdoor and indoor datasets show that our method outperforms the recent methods in terms of matching performance and computational efficiency. The code is available at https://github.com/TruongKhang/TopicFM.

1. Introduction

Image matching is a long-standing problem in computer vision. It aims to find pixel-level correspondences across two or more images. With a rapid growth of deep learning in recent years, the matching algorithm is transformed from a complex multi-step pipeline to a single end-to-end deep neural network. In particular, the conventional methods usually involve the following steps: local feature/keypoint detection, feature/keypoint description, matching, and outlier rejection [4, 24, 29, 36, 45, 58]. Meanwhile, recent learning-based methods extract dense feature maps from the image pair and then perform matching to find correspondences [25, 39, 40]. Compared to the keypoint detector-based methods [17, 44], the dense methods can produce a huge number of correspondences, thus achieve state-of-the-art performance. They focus on learning robust and distinctive representation for accurate matching, and apply a coarse-to-fine strategy to achieve computational efficiency [50, 55, 66]. However, these methods still require a high computational power because of using a very deep network for feature extraction [66] or applying Transfomers to whole images [50, 55]. We find that the non-overlapping regions between images are redundant when learning robust features. Moreover, a main drawback of these current end-to-end methods is the lack of interpretability of matching models. They simply perform an exhaustive search among all features of whole images to find the potential matches. This is quite different from human perception. When humans observe a pair of images, they can quickly recognize the co-visible regions or objects of image pair and then only need to find matching points in these regions.

In this paper, we imitate the human cognitive system above by designing a novel feature matching architecture, called TopicFM. Inspired from topic modeling in data mining [7, 57], we assume that the spatial structures, objects appearing in all images of dataset are semantically organized into a set of topics, in which each topic reasons about a specific kind of structures. It is also observed that each image is combined from several topics, which is naturally derived from human cognition. For instance, when seeing an image, humans can quickly describe about the structures or shapes, i.e., topics mentioned in that image. Therefore, for each pair of images, our method first discovers the hidden topics of each image. We represent a topic by a global embedding vector. The global topic is then updated by observed image to obtain a local representation. Based on this, we can estimate a distribution over topics for each feature pixel by measuring the distance between the feature and topic embeddings. As a result, we probabilistically assign each feature to a proper topic, thus form local image structures in each topic. Fig. 1 illustrates the most important topics inferred from an image pair, in which each topic presents a kind of local structure in images. Moreover, the same structures in both images are assigned to a same topic, which make the topic interpretable.

After topic inference for each image, we only need to select co-visibility topics of image pair to augment features...
Figure 1. The main idea of our human-friendly topic-assisted feature matching. We interpret each image via a set of topics/structures marked in different colors, and then quickly recognize the same content across sequence of images (e.g., orange box). After understanding about these structures, we leverage the distinctive information of each topic to enhance the pixel-level representation, thus boosts the matching performance as shown in the second row.

for accurate matching. We refer this matching method as structural feature matching because we encode the structure information into features via topics. Our approach has three advantages. First, it can remove redundancy in matching by ignoring the invisible regions between two images. Second, the method can encode explicitly the shape and geometric information of image objects to learn robust features while the previous works applied Transformers to entire images for learning global context information without interpretability [44, 50, 55]. As a consequence, the final advantage of our method is interpretable because we can explain image structures used for matching.

Go one step further, we design an efficient end-to-end architecture for image matching. Similar to recent works [23, 50, 55, 66], our proposed network applies a coarse-to-fine framework which first detects the correspondences at a low resolution of images and then refines them inside cropped patches at high resolution. However, our method is more efficient because we use smaller networks in both coarse and fine stages. In particular, we apply a standard Unet for feature extraction instead of Res-Unet [50, 66]. Also, our feature matching module, TopicFM, consumes less computation than the Transformer-based networks [44, 50, 55].

The contribution of this paper is fourfold

- We formulate semantic structures across all images of dataset into global topics. These topics are used to infer the structures of each image, thus make our matching model interpretable.

- We then propose a structural feature matching module, namely TopicFM, which first estimate co-visibility topics using latent variables and then augment features in these topics to find reliable matches.

- We design an efficient end-to-end architecture for image matching, our source code is publicly available.

- We demonstrate the effectiveness of our method through extensive experiments. We also show the interpretability of our method that can categorize a same spatial structure across images into a same topic.

2. Related Works

Image Matching. Following Jiayi Ma et. al. [32], traditional image matching can be classified into area-based method and feature-based method, in which feature-based method is widely used due to its efficient and robustness. The common pipeline of feature-based matching first detects a set of keypoints, describes each of them by a high-dimensional feature vector, and then performs a matching algorithm to find correspondences between two sets of feature points. The correspondences can be refined further by using an outlier rejection.

For feature detection and description, some well-known traditional algorithms such as SIFT [29], SURF [4], FAST [41], [9] are still applied in some applications nowadays. However, traditional methods require a complicated selection of hyperparameters to achieve good performance [19]. Twelve years after SIFT, a fully learning-based architecture LIFT [58] was proposed to address hand-crafting step in traditional approach. Learning-based approach starts to become dominant and attract a lot of studies [5, 17, 18, 36, 38, 53]. However, these methods mostly adopt standard CNNs to learn features from local context information which is less effective when processing low-textured images. To address this issue, several architectures [23, 30, 31, 50, 55] encode a global context to learn features. ContextDesc [30] introduced geometric context encoder using a large patch sampler while ALSFeat [31] applied deformable CNN. LoFTR [50] applied Transformers with self- and cross- attentions to extract dense feature maps. Although these aforementioned methods are technically sound, they do not explain about the exact context or geometric information
used to encode into features and thus lack interpretability. In contrast, our method observes the spatial structure of objects and shapes organized in topics, which is more interpretable.

Given two sets of features produced by the detection-description methods above, a basic feature matching algorithm applied a nearest neighbor search [34] or ratio test [29] to find potential correspondences. After that, outlier rejection algorithms such as RANSAC [2, 13, 20], consensus- or motion-based heuristics [6, 8, 10, 28], or learning-based [51, 59, 60] are used to extract final matches. A main drawback of these methods is that the performance is based on the robustness of features learned in previous steps. Recently, several works proposed [12, 44, 47] to use attentional graph neural network (GNN) to enhance features and then perform matching with an optimal transport layer [15, 35, 37, 48]. However, due to focusing on feature matching only, these methods still depend on a feature detector, which is not flexible.

Motivated by the above observation, end-to-end methods [23, 50, 55, 66] are proposed to solve image matching in a single forward pass instead of dividing many steps separately. They had to process dense feature maps; therefore, a coarse-to-fine strategy is applied to achieve computational efficiency. Patch2Pix [66] detected coarse matches in a low-resolution and then refined them gradually at higher resolution. Similarly, the other coarse-to-fine methods [23, 50, 55] learned robust and distinctive features by using transformers and achieved the state-of-the-art performance. However, they are still inefficient when propagating the global context information from whole images. We argue that the invisible regions between the image pair are redundant and might cause noise when learning features with transformers. Therefore, we proposed a topic modeling approach to utilize adequate context cues for learning representation.

**Interpretable Image Matching.** Interpretability of vision models has been an active research recently [3, 11, 46, 65]. It aims to reason about a certain decision or prediction in image recognition [54, 56, 61, 62], deep metric learning [64]. In image matching, the detector-based methods [21, 29] could estimate the interpretable feature keypoints which are corners, blobs, or ridges. However, these methods could not explain spatial structures such as objects, shapes of detected features. Otherwise, existing end-to-end methods only extracted dense feature maps using local context via CNNs [66] or global context via transformers [50, 55] which did not provide about how much the context information are observed, thus lacked of interpretability. In contrast, humans can identify the feature keypoints by observing different spatial structures in images and then pointing out the keypoints in each structure. Inspired from this cognitive process, our method designs an end-to-end model in a human-friendly way which categorizes local structures of images into different topics and then only uses the information within topics to augment features. Moreover, our method can select important topics which contain co-visible regions of two images for interpretable matching. To the best of our knowledge, our method is the first work introducing interpretability to image matching task explicitly.

### 3. Proposed Method

#### 3.1. Coarse-to-fine Architecture

We introduce an end-to-end architecture which estimates correspondences between two images in a coarse-to-fine manner. Similar to most recent methods [50, 55, 66], our coarse stage first estimates coarse matches at a low image resolution, upscals and crops patches around those coarse coordinates at the high resolution. Then we refine the coordinates inside patches in the fine stage. Fig. 2 illustrates our architecture which can be summarized into three steps. Firstly, we extract dense feature maps with an Unet-liked architecture. Secondly, we estimate a set of coarse matches by first estimating the matching distribution via an interpretable module called TopicFM and then finding correspondences based on the estimated probability. Finally, we refine the coarse matches in fine stage at the high image-resolution.

**Initial feature extraction.** Given an image pair \( I^A, I^B \), we apply an Unet with 4 down-upsampling steps to extract dense feature maps at different resolutions. We then perform coarse and fine matching at \( \frac{1}{8} \) and \( \frac{1}{4} \) image-resolution respectively. This design is most similar to LoFTR [50], but we adopt a standard convolution block instead of ResNet block as in LoFTR to reduce computation.

**TopicFM.** The initial features extracted from CNN module above only consider local context information. This module aims to improve representation power for accurate matching by leveraging the spatial structures. We propose to estimate the match distribution through two steps. First, we infer the topics/structures contained in each image by using Transformers in which the topics are queries. Note that the set of topics are global and shared across images in dataset. This is a similar concept with topic modeling in data mining [7, 57]. Second, based on structural awareness in each topic, we then augment features and compute the matching probability. The details of two-step TopicFM are described in Section 3.2.

**Finding correspondences.** Given the matching probabilities of feature pair, this step simply uses a threshold to select the pairs with high similarity as correspondences.

**Refinement inside patches.** After determining coarse matches through three steps above, we refine them at high resolution. We first upscale the coarse coordinates and then crop a \( N_p \times N_p \) patch from the high-level feature map centered at each estimated coordinate. Similar to [50], we ap-
Figure 2. Overview of proposed architecture. We extract multi-level feature maps via an UNet and then perform coarse-to-fine matching. In coarse stage, we consider each feature pixel as a “word” and use topic modeling to assign each feature to a topic. After that, the features in each topic are augmented to estimate matching probability. After coarse matches extracted by high-confidence thresholding, we refine the coordinates inside the cropped patches at high resolution.

3.2. Topic-assisted Feature Matching

3.2.1 Preliminaries: Probabilistic Feature Matching.

Two coarse feature maps $F^A_c, F^B_c$ extracted from Unet can be regarded as two bag-of-visual-words [14, 49], i.e., each feature vector is a visual word. Note that each feature can be equipped with a positional encoding vector to preserve spatial information. Let $m_{ij}$ be a random variable indicating an event that the feature $F^A_{c,i}$ is matched to the feature $F^B_{c,j}$. Given two feature sets, our goal is to estimate a match distribution $M = \{m_{ij}\}$ [5]

$$P(M \mid F^A_c, F^B_c) = \prod_{m_{ij} \in M} P(m_{ij} \mid F^A_c, F^B_c) \quad (1)$$

Existing methods [5, 44, 50] computed feature similarities and then used Softmax [5], Dual-Softmax [50], or optimal transport with Signkhorn regularization [44] to output the matching probabilities. Different from them, our TopicFM computes this distribution by introducing hidden topics/structures.

3.2.2 Topic Inference via Transformers

Assume that the spatial structures inside all images of dataset are categorized into $K$ topics. For each topic $k$, we represent it with a topic embedding $T_k$. $T_k$ is trainable. It is also observed that each image contains a set of specific shapes, structures derived from different topics. To discover these individual structures, we assign a topic for each feature pixel in a probabilistic way. Let $z_i$ and $\theta_i$ be topic indicator and topic distribution for the feature $F_i$ respectively, where $z_i \in \{1, \ldots, K\}$ and $\theta_{i,k} = p(z_i = k \mid F_i)$ being the probability for assigning $F_i$ to topic $k$. To estimate $\theta_i$, we infer the local topic representations $\hat{T}$ from the global representations $T$ via Transformers and then compute the distance between the feature $F_i$ and the individual topics $\hat{T}_k$ as follows

$$\hat{T}_k = T(T_k, F) \quad (2)$$
$$\theta_{i,k} = \langle \hat{T}_k, F_i \rangle \sum_{h=1}^{K} \langle \hat{T}_h, F_i \rangle \quad (3)$$

where $T(T_k, F)$ is a Transformer block with queries $T_k$, keys $F$, and values $F$. This function is used to collect relevant information from image to each topic.

3.2.3 Structural Feature Augmentation

This section describes how to compute Eq. 1 using the topics inferred above. For each feature pair $(F^A_{c,i}, F^B_{c,j})$, we denote $z_{ij}$ as a topic assignment indicating that whether two features are assigned to a same topic or not. $z_{ij} \in \mathcal{Z} = \{1, 2, \ldots, K, NaN\}$. If $z_{ij} = k$ ($k = 1 \ldots K$), this means that the pair belongs to a same topic $k$. Otherwise, $z_{ij} = NaN$ indicates the pair is not in a same topic, thus is highly unmatchable.
We use latent variables \( z_{ij} \) to compute the match distribution in Eq. 1 as follows,

\[
\log P (M \mid F_A^c, F_B^c) = \sum_{m_{ij} \in M} \log P (m_{ij} \mid F_A^c, F_B^c)
\]

\[
= \sum_{m_{ij} \in M} \log \sum_{k \in \mathbb{Z}} P (m_{ij}, z_{ij} = k \mid F_A^c, F_B^c) \tag{4}
\]

To compute Eq. 4, we approximate it with an Evidence Lower Bound (ELBO)

\[
\mathcal{L}_{ELBO} = \sum_{m_{ij}} P (z_{ij} = k \mid F_c) \log P (m_{ij} \mid z_{ij}, F_c) = \mathbb{E}_{p(z_{ij})} \log P (m_{ij} \mid z_{ij}, F_A^c, F_B^c) \tag{5}
\]

\( P (m_{ij} \mid z_{ij}, F_A^c, F_B^c) \) refers to the matching probability conditioned on the topic \( z_{ij} \) which encodes the context information of structures, shapes. Eq. 5 can be estimated by applying Monte-Carlo (MC) sampling

\[
l_{ij} = \frac{1}{S} \sum_{s=1}^{S} \log P \left( m_{ij} \mid z_{ij}^{(s)} , F_A^c, F_B^c \right) \tag{6}
\]

\[
z_{ij}^{(s)} \sim P \left( z_{ij} \mid F_A^c, F_B^c \right) \tag{7}
\]

The main goal now is to compute the topic distribution of feature pair, \( P(z_{ij} \mid F_A^c, F_B^c) \), and the conditional matching distribution \( P(m_{ij} \mid z_{ij}^{(s)} , F_A^c, F_B^c) \).

**Topic distribution.** We estimate the distribution of \( z_{ij} \) by factorizing it into two distributions of \( z_i \) and \( z_j \) as follows

\[
P (z_{ij} = k \mid F_A^c, F_B^c) = P (z_i = k \mid F_A^c) P (z_j = k \mid F_B^c) = \theta_i^A \theta_j^B \]  \tag{8}

where \( \theta_i^A, \theta_j^B \) are computed from Eq. 2, 3. Note that Eq. 8 above is the probability for assigning the feature pair to a specific topic \( k \in \{1 \ldots K \} \). As a result, we can compute the probability of being in at least one topic by

\[
P (z_{ij} \in \{1, \ldots, K \} \mid F_A^c, F_B^c) = \sum_{k=1}^{K} \theta_i^A \theta_j^B \]  \tag{9}

Otherwise, the probability for not being in same topic is

\[
P (z_{ij} = NaN \mid . ) = 1 - \sum_{k=1}^{K} P (z_{ij} = k \mid . ) = 1 - \sum_{k=1}^{K} \theta_i^A \theta_j^B \]  \tag{10}

In summary, the topic distribution for each pair of features is determined as follows

\[
P (z_{ij} = k \mid F_c) = \begin{cases} 
\theta_i^A \theta_j^B & k \in \{1 \ldots K \} \\
1 - \sum_{k=1}^{K} \theta_i^A \theta_j^B & k = NaN
\end{cases}
\]

We can sample \( z_{ij}^{(s)} \) from this distribution by sampling \( z_i^{(s)}, z_j^{(s)} \) from \( \theta_i^A, \theta_j^B \) separately because of the i.i.d. assumption,

\[
z_{ij}^{(s)} = \begin{cases} 
\hat{k} & \text{if } z_i^{(s)} = z_j^{(s)} = k \\
NaN & \text{if } z_i^{(s)} \neq z_j^{(s)}
\end{cases}
\]

**Conditional matching distribution.** After the sampling step, we can divide two sets of features into topics. The features inside each topic represent a specific kind of spatial structure. More interestingly, the co-visibility features of image pair are also organized in the same topic because they all reflect a same semantic content. Based on these observations, we propose to augment the features using the context information of each topic. Let \( F_A^{c,k} \) and \( F_B^{c,k} \) be two feature sets of a sampled topic \( k = z_{ij}^{(s)} \). To compute the distribution \( P(m_{ij} \mid z_i^{(s)} = k, F_A^c, F_B^c) \), we strengthen the features by applying self- and cross-attention of Transformer [44, 50]

\[
F_A^{c,k} \leftarrow \mathcal{T} \left( F_{c,i}^{A,k}, F_{c,j}^{B,k} \right), \quad F_B^{B,k} \leftarrow \mathcal{T} \left( F_{c,j}^{B,k}, F_{c,j}^{B,k} \right)
\]

Then the matching probability is determined by simply computing feature distance and normalizing it with a Dual-Softmax [50].

\[
P(m_{ij} \mid z_i^{(s)} = k, F_A^c, F_B^c) = \text{DualSoftmax} \left( \langle F_{c,i}^{A,k}, F_{c,j}^{B,k} \rangle \right)
\]

To reduce the redundant computation, we only need to augment features in the co-visibility topics of the image pair. We select these topics by comparing the topic distributions of two images. First, we estimate the topic distribution at image-level by simply aggregating the distributions of all features.

\[
\theta_k^A \propto \sum_{i=1}^{\left| F_A^c \right|} \theta_{i,k}^A, \quad \theta_k^B \propto \sum_{j=1}^{\left| F_B^c \right|} \theta_{j,k}^B
\]

where \( \propto \) is the normalization operator. It is observed that a topic \( k \) is covisible when it is perceived in both images. Therefore, we can estimate the probability of co-visibility by multiplying two distributions together, \( \theta^{vis} = \theta^A \theta^B \). As a result, the highest important topics are selected for feature augmentation.
| Method                  | Homo. Est. AUC (%) | #Matches |
|------------------------|--------------------|----------|
|                        | 3px                | 5px      | 10px     |
| D2Net [18] + NN        | 23.2               | 35.9     | 53.6     | 0.2K |
| R2D2 [38] + NN         | 50.6               | 63.9     | 76.8     | 0.5K |
| DISK [53] + NN         | 52.3               | 64.9     | 78.9     | 1.1K |
| SP [17] + SuperGlue [44]| 53.9               | 68.4     | 81.7     | 0.6K |
|Sparse-NCNet [39]       | 48.9               | 54.2     | 67.1     | 1.0K |
| DRC-Net [25]           | 50.6               | 56.2     | 68.3     | 1.0K |
| Patch2Pix [66]         | 59.3               | 70.6     | 81.2     | 0.7K |
| LoFTR [50]             | 65.9               | 75.6     | 84.6     | 1.0K |
| TopicFM (Ours)         | 67.2               | 76.9     | 85.4     | 1.0K |

Table 1. Evaluation of homography estimation on HPatches [1]. We compute AUC metrics following [50].

Figure 3. Mean Matching Accuracy (MMA) computed on HPatches. We report the results when changing thresholds from 1 to 10 pixels. TopicFM outperforms the others from [1,5] pixels.

3.3. Training Loss

Coarse loss. Given a set of ground truth matches \( M_c \) at coarse level, we label each ground truth pair by 1. The predicted matching probability is given in Eq. 6,7,8,9. The loss for positive samples has this form

\[
L^\text{pos}_c = - \sum_{m_{ij} \in M_c} \left( E_{p}(z_{ij}) \log P(m_{ij} \mid z_{ij}, F_c^A, F_c^B) \right) - \log \sum_{k=1}^{K} \theta_{i,k}^A \theta_{j,k}^B 
\]

(11)

where the first term is the ELBO loss in Eq. 6 and the second term is used to enforce the pair into a same topic which is derived from Eq. 9.

We also need to add a negative loss to prevent assigning all features into an unique topic. For each ground truth match \( m_{ij} \), we sample \( N \) unmatched pairs \( \{m_{in}\}_{n=1}^{N} \) and then define the negative loss using Eq. 10,

\[
L^\text{neg}_c = - \sum_{m_{ij}} \left( \frac{1}{N} \sum_{n=1}^{N} \log \left( 1 - \sum_{k=1}^{K} \theta_{i,k}^A \theta_{j,k}^B \right) \right) 
\]

(12)

The final loss in the coarse stage is combined by two terms \( L_c = L^\text{pos}_c + L^\text{neg}_c \).

Fine Loss. After estimating a set of correspondences at coarse level, we crop a patch centered at each coarse match and then refine the matching coordinates inside the patch. We compare these refined coordinates with ground truths by using \( L_2 \) loss similar to [50].

4. Experiments

4.1. Implementation Details

Training. Our end-to-end architecture is trained on the MegaDepth dataset [26], in which the highest dimension of each image is resized to 800. We use 4 GPUs to train the model with a batch size of 4, each GPU has 11GB memory. Compared to the recent Transformer-based network LoFTR which requires approximately 24GB of each GPU, our architecture is much more efficient and suitable when only having the limited resources. We implement our network in PyTorch with an initial learning rate of 0.01. For the network hyperparameters, we set the number of topics \( K \) to 100, the threshold of coarse match selection \( \tau \) to 0.2, and the number of co-visibility topics for feature augmentation \( K_{co} \) to 6.

Evaluation. We evaluate the image matching performance on three tasks: homography estimation, relative pose estimation, and visual localization. All these experiments
used the pre-trained model of MegaDepth without fine-tuning. However, some hyperparameters can be modified when testing including the coarse match threshold $\tau$, number of co-visibility topics $K_{co}$.

### 4.2. Benchmark Performance

**Homography estimation.** The homography matrix between two images can be estimated by an algorithm given the correspondences. To assess the estimation, we use the HPatches dataset [1]. For each image pair, we first warp four corners of the first image to the second image using both estimated and ground truth homography, and then compute the corner error between two warped versions [17]. We measure the accuracy by computing the area-under-the-curve (AUC) metric when thresholding the corner error with $\{3, 5, 10\}$ pixels [44]. Table 1 compare our method with recent state-of-the-art methods. Note that the results are computed following the similar setups in [50]. Our method mostly outperformed the others which demonstrates its effectiveness. Moreover, we also evaluate image matching performance on HPatches following the settings in [66]. Fig. 3 shows the mean matching accuracy (MMA) of all methods. We observe that our TopicFM can achieve a very high accuracy in overall, especially at small thresholds $[1, 5]$ of pixel error.

**Relative pose estimation.** This task is used to estimate a transformation matrix between two images. We evaluate the performance in both indoor and outdoor datasets, corresponding to MegaDepth [26] and ScanNet [16] respectively. The test set of each dataset includes 1500 image pairs. We use a resolution of $640 \times 480$ for ScanNet and a resolution of 1200 for the longer dimension of images in MegaDepth. Similar to [44, 50], the metric used in this experiment is AUC of the pose error at thresholds of $[5^\circ, 10^\circ, 20^\circ]$). Table 2 and 3 reveal our results on MegaDepth and ScanNet respectively. To make a fair comparison with most recent coarse-to-fine methods on ScanNet, we only report the results using the model trained only on MegaDepth without fine-tuning. As presented in Table 2 and 3, our method is better than the other coarse-to-fine baselines [25, 50, 55, 66] in all evaluation metrics. Compared to the combination of the robust feature detector SuperPoint (SP) [17] and robust feature matching SuperGlue [44], we only have a worse performance at $20^\circ$ of AUC on ScanNet. The main reason is that SuperGlue is trained directly on ScanNet. However, TopicFM is still better than SP+SuperGlue in overall.

A qualitative evaluation between our method and the other coarse-to-fine methods including Patch2Pix [66], LoFTR [50] is presented in Fig. 4. The figure demonstrates that TopicFM is better than the baselines when performing matching in several challenging conditions of images such as the large relative captured viewpoints (MegaDepth) or the dark, untextured scenes (ScanNet).

**Visual Localization.** Different from relative pose es-

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Table 4. The results of visual localization on Aachen Day-Night v1.1 [63] using the HLoc pipeline [43]

| Method                   | Day    | Night  | overall  |
|--------------------------|--------|--------|----------|
| ISRF [33]                | 87.1/94.7/99.7 | 74.3/96.4/97.9 | 89.8     |
| KAPTURE + R2D2 [22]      | 90.0/96.2/99.9 | 72.3/98.6/97.9 | 90.4     |
| APCGm [22]               | 89.8/96.1/99.9 | 77.0/97.6/99.9 | 92.1     |
| SP [17]+SuperGlue [44]   | 86.4/93.6/97.7 | 72.5/98.5/97.7 | 89.2     |
| Patch2Pix [66]           | 88.7/95.6/99.9 | 78.7/98.6/99.9 | 91.9     |
| LoFTR [50]               | -      | -      | -        |
| MatchFormer [55]         | 90.5/95.9/99.9 | 77.0/91.1/99.5 | 92.1     |

Table 5. Visual localization on InLoc dataset [52] using HLoc pipeline. We achieve best performance in overall.

| Method                   | DUC1   | DUC2   | overall  |
|--------------------------|--------|--------|----------|
| ISRF [33]                | 39.4/58.1/70.2 | 41.2/61.1/69.5 | 56.6     |
| KAPTURE + R2D2 [22]      | 41.4/60.1/73.7 | 47.3/67.2/73.3 | 60.5     |
| SP [17]+SuperGlue [44]   | 49.0/68.6/78.8 | 53.4/77.1/82.4 | 68.6     |
| Patch2Pix [66]           | 44.4/66.7/78.3 | 49.6/64.9/72.5 | 62.7     |
| LoFTR [50]               | 47.5/72.8/84.8 | 54.2/74.8/85.5 | 69.8     |
| MatchFormer [55]         | 46.5/73.9/85.9 | 55.7/77.1/81.7 | 69.1     |
| TopicFM                  | 52.0/74.7/87.4 | 53.7/74.8/83.2 | 70.9     |
Figure 5. Topic visualization across images and datasets. Our method can model a specific kind of structure by a topic which then supports the matching process effectively as described in Section 3.2.

timation, visual localization estimates a camera pose for each image in a global coordinate system, yet involves several steps. The pipeline first builds a 3D structure of the scene from a set of database images. Next, given an input query image, it registers this image into the database and finds a set of 2D-3D matches which is then used to output the pose of query image. In these steps, finding correspondences plays an important role. Therefore, we plug the matching method to a visual localization pipeline to evaluate the matching performance. Following [50, 66], we use a full localization pipeline with HLoc [43]. The benchmark datasets are the Aachen Day-Night v1.1 [63] containing of outdoor images and the InLoc [52] dataset with indoor scenes. We obtain the results of all these experiments by using the image-matching-toolbox [66].

Table 4, 5 present the results for the Aachen v1.1 and InLoc dataset, respectively. Our method achieved a competitive performance in both two benchmarks compared to the state-of-the-art baselines. As shown in Table 4, TopicFM perform on par with the SP+SuperGlue in overall. SP and SuperGlue are trained by leveraging different kind of datasets with various shapes and scenes such as MS-COCO 2014 [27] (SP), Synthetic Shapes [17] (SP), and MegaDepth [26] (SuperGlue). Compared to the second-best method LoFTR, our overall result is slightly better. The main reason of achieving good performance of LoFTR is that LoFTR was fine-tuned by augmenting color images of MegaDepth to fit the night-time images. In contrast to all aforementioned setups, our method only uses a unified model trained on MegaDepth. This demonstrates the robustness of proposed architecture. Similarly, for the InLoc evaluation shown in Table 5, our method is better all baselines on the DUC1 set with a large margin although it is worse on the DUC2 set. However, we still achieve the best performance on average.

4.3. Interpretability Visualization

We visualize the inferred topics to demonstrate the interpretability of our model. As shown in Fig. 5, our method can partition the contents of image into different kind of spatial structures in which the similar contents are assigned to a same topic. For instance, the topic “human” is marked in green color in the first image pair of MegaDepth and Aachen, the “tree” is marked in orange, the “ground” is in blue. Specially, the different parts of a building with such as roofs, windows, pillars, etc. are separated in different topics respectively. This phenomenon is repeated across images of MegaDepth and Aachen Day-Night which demonstrating the effectiveness of our topic modeling and topic inference modules. Notably, as illustrated in the third image pair of first two rows in Fig. 5, our method can focus on the co-visibility structures in a same topic (marked with color) and ignore the non-overlap information (marked without color). Although TopicFM is trained on the outdoor dataset MegaDepth, it still can generalize well on the indoor dataset ScanNet as shown in the last row of Fig. 5.

4.4. Ablation Study

Number of Topics K. We conduct an experiment to analyze how the number of topics used in TopicFM effects performance. Table 6 shows the evaluation results on MegaDepth when using $K \in \{10, 20, 50, 80, 100\}$. We use same hyperparameters for all setups and compute AUCs similar to the experiment of MegaDepth above. We train each model of K using 30% of training set to quickly obtain the results. As observed in Table 6, the best performance is achieved when K is about 50. Using a small or large number of topics K does not benefit the performance because of the underfitting or overfitting problem respectively.

Co-visibility Topics. In section 3.2, we estimated topic probabilities of image pair to select most important topics
Table 6. Impact of the number of topics and co-visibility-topics.

| $K$ | AUC on MegaDepth | $K_{co}$ | AUC on MegaDepth |
|-----|------------------|---------|------------------|
|     | $5°$            | $10°$   | $20°$            | $5°$            | $10°$   | $20°$ |
| 10  | 48.6            | 65.4    | 78.3            | 2               | 49.3    | 66.1    | 78.6 |
| 20  | 49.1            | 65.3    | 77.8            | 6               | 52.7    | 69.0    | 81.1 |
| 50  | 49.1            | 66.2    | 78.7            | 8               | 53.3    | 69.6    | 81.2 |
| 80  | 49.1            | 65.7    | 78.1            | 10              | 54.1    | 70.1    | 81.6 |
| 100 | 49.0            | 65.6    | 77.9            | 12              | 53.7    | 69.8    | 81.4 |

Table 7. Efficiency analysis of coarse-to-fine methods.

| Method     | Runtime Benchmark (ms) | 640 × 480 | 896 × 672 | 1200 × 896 |
|------------|------------------------|-----------|-----------|-----------|
| Patch2Pix  | 228                    | 659       | 1935      |
| LoFTR      | 100                    | 232       | 500       |
| D2Net      | 75                     | 172       | 332       |

containing co-visibility information for matching. Therefore, the number of co-visibility topics $K_{co}$ also has an impact to the overall matching performance. To analyze this, we evaluate on MegaDepth as same as the Relative Pose Estimation of Section 4.2 when changing $K_{co} \in \{2, 4, 6, 8, 10, 12\}$. As shown in Table 6, the performance is gradually increased when $K_{co}$ is increased. However, it starts to drop when $K_{co}$ is higher than 10 because all co-visibility information now is visited.

**Run-time comparison.** We compare the efficiency of our method with the recent coarse-to-fine architectures including Patch2Pix [66] and LoFTR [50]. As shown in Table 7, TopicFM is more efficient compared to LoFTR and especially to Patch2Pix. At the high-resolution images 1200 × 896, our runtime is reduced about 35% and 83% compared to LoFTR and Patch2Pix respectively.

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