TCDesc: Learning Topology Consistent Descriptors

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ABSTRACT

Triplet loss is widely used for learning local descriptors from image patch. However, triplet loss only minimizes the Euclidean distance between matching descriptors and maximizes that between the non-matching descriptors, which neglects the topology similarity between two descriptor sets. In this paper, we propose topology measure besides Euclidean distance to learn topology consistent descriptors by considering kNN descriptors of positive sample. First we establish a novel topology vector for each descriptor followed by Locally Linear Embedding (LLE) to indicate the topological relation among the descriptor and its kNN descriptors. Then, we define topology distance between descriptors as the difference of their topology vectors. Last we employ the dynamic weighting strategy to fuse Euclidean distance and topology distance of matching descriptors and take the fusion result as the positive sample distance in the triplet loss. Experimental results on several benchmarks show that our method performs better than state-of-the-arts results and effectively improves the performance of triplet loss.

1 INTRODUCTION

Image matching is a fundamental computer vision problem and the crucial step in augmented reality (AR) [6, 40] and simultaneous localization and mapping (SLAM) [30, 31], which is usually consists of two steps: detecting the feature points and matching feature descriptors. The robust and discriminative descriptors are essential for accurate image matching. Early works mainly focus on the handcrafted descriptors. SIFT [22] maybe is the most successful handcrafted descriptor which has been proven effective in various areas [7, 39, 50]. Meanwhile, the binary descriptors [5] are proposed to reduce storage and accelerate matching. However, handcrafted descriptors are not robust enough due to the lack of high-level semantic information.

Recently with the successful application of CNN in multiple fields [3, 12, 19], researchers [14, 27, 35, 37, 47] try to learn descriptors directly from image patch by using CNN. Recent works [27, 42, 48] mainly focus on learning descriptors using triplet loss [33] to encourage Euclidean distance of negative samples is a margin larger than that of positive samples, where negative samples and positive samples denote the non-matching descriptors and matching descriptors respectively. Specifically, CNN takes two image patch sets with one-to-one matching relationship as input and outputs corresponding two descriptors sets, where the Euclidean distance of matching descriptors is minimized and that of non-matching descriptors is maximized.

However, as shown in Fig. 1a, triplet loss of former works only considers Euclidean distance between descriptors and completely neglects the neighborhood information of descriptors. There exists topology difference between matching descriptors because former triplet loss only considers Euclidean distance between descriptors and completely neglects the neighborhood information of descriptors. In (b), our method encourages similar linear topology between matching descriptors, which means the matching descriptors have the matching kNN descriptors and the similar linear combination weights.

![Figure 1: Distribution of descriptors learned by (a) former triplet loss and (b) our method. In (a), there exists topology difference between two matching descriptors because former triplet loss only considers Euclidean distance between descriptors and completely neglects the neighborhood information of descriptors. In (b), our method encourages similar linear topology between matching descriptors, which means the matching descriptors have the matching kNN descriptors and the similar linear combination weights.](image-url)
dimensionality reduction, while this topology vector depicts the linear topology among the descriptor and its \( k \)NN descriptors. Then we take the \( l_1 \) distance of descriptors’ topology vectors as their topology distance to indicate the neighborhood difference between descriptors. Last we modify the positive sample distance in the triplet loss as the dynamic weighting of Euclidean distance and topology distance of matching descriptors. The consistent topology between matching descriptors is encouraged with their topology distance minimized.

Compared with former triplet loss, our method learns more robust descriptors since we take additional \( k \)NN descriptors of matching descriptors for CNN’s back-propagation. Otherwise, our method modifies and consummates the distance measure of positive samples for triplet loss, which means our method can improve performance of many other algorithms of learning descriptors using triplet loss. The generalization of our method is verified in several benchmarks in Section 4.

The contributions of this paper are three-fold:

- We establish a novel topology vector for each descriptor followed by LLE [32] and define the topology distance between descriptors to indicate their neighborhood difference.
- We employ the dynamic weighting strategy to fuse Euclidean distance and topology distance of matching descriptors and take the fusion result as the positive sample distance in the triplet loss.
- The experimental results verify the generalization of our method. We test our method on the basis of HardNet [27] and CDF [48], and experimental results show our method can improve their performance in several benchmarks.

2 RELATED WORK

In this section, we begin by discussing the related work in the image hashing domain, with main focus towards the motivation behind adversarial autoencoders. Then, we continue our discussion on adversarial learning and their limitations, especially on their generalization property when matching to the target distribution (or sample complexity requirement).

2.1 Learning-based Descriptors

Perhaps SIFT [22] is the most successful and widely used handcrafted descriptor, however, all handcrafted descriptors, including SIFT [22], LIOOP [43], GLOHP [26], DAISYP [45], DSP-SIFTP [8] and BRIEF [5] are not robust enough as they only consider the pixel-level information instead of the high-level semantic information. In the past several years, learning-based descriptors outperforms handcrafted descriptors in image matching [10, 34] and image retrieval [13, 44] benefitting from powerful semantic representation of CNN.

L2-Net [37] proposes a CNN architecture with 7 convolutional layers and a Local Response Normalization layer to normalize descriptors, and this architecture is employed by many works [27, 38, 48] including ours. HardNet [27] implements a hard negative mining method for learning descriptors by maximizing the nearest non-matching descriptors using triplet loss. CDbin [46] combines triplet loss and other three losses for learning descriptors and explores the performance of descriptors with different lengths. SOSNet [38] proposes the Second Order Similarity Regularization in the basis of triplet loss to learn more compact descriptors. Exp-TLoss [42] modifies triplet loss and proposes a novel exponential losses to mine harder positive samples as focal loss [21]. CDF [48] replaces the hard margin with a non-parametric soft margin with the dynamic triplet weighting to avoid the sub-optimal results. However, all of them fail to maintain the similar topology between matching descriptors as our work, which contributes to the more robust descriptors.

2.2 Triplet Loss

Triplet loss consists of three parts: margin, distance of positive samples and distance of negative samples, which updates networks by encouraging distance of negative samples is a margin larger than distance of positive samples.

FaceNet [33] first proposes triplet loss and applies it in face recognition. Alexander [16] implements the hard triplets mining method for Person Re-Identification, which defines the hardest positive sample as positive sample with the largest distance and define the hardest negative sample as negative sample with smallest distance. Wang [41] combines the triplet loss and softmax loss to learn more discriminative features for Person Re-Identification. Otherwise, triplet loss has been proven effective in image retrieval [20] and learning descriptors [27, 38, 42, 48].

However, former triplet loss takes Euclidean distance between samples as the only measure, which completely neglects the topology of samples. In this work, we propose a novel topology measure for triplet loss with considering neighborhood information of positive samples and verify its effectiveness on learning descriptors.

2.3 Manifold Learning

Manifold Learning [2, 9, 11, 32, 36, 49] is a commonly used dimensionality reduction method which tries to keep similar manifold between high-dimensional data and low-dimensional data. Laplacian Eigenmaps [2] tries to preserve the graph structure of high-dimensional data in low-dimensional data using spectral techniques. ISOMap [36] encourages high-dimensional data and low-dimensional data have the same geodesic distance instead of Euclidean distance, where the geodesic distance means the shortest path connecting two data sample in its \( k \)NN graph. Compared with ISOMap using the global information, LLE [32] only tries to keep the similar locally linear combination weight between high-dimensional data and low-dimensional data. Undoubtedly ISOMap is much more time-consuming.

Manifold learning also plays an important role in recent deep learning algorithms. Ahmet [17] implements a hard training example mining method which takes manifold nearest neighbors but not Euclidean neighbors as the hard positive samples and Euclidean neighbors but not manifold nearest neighbor as the hard negative samples. Jiwen Lu [23] proposes a multi-manifold deep metric learning method for image set classification by nonlinearly mapping multiple sets of image instances into a shared feature subspace. The above methods mainly focus on image retrieval or image classification, and we are the first to introduce manifold learning into descriptors learning and image matching.
3 METHODOLOGY

In this section, we first review the method of learning descriptors using triplet loss in Section 3.1, and then we present the establishment of our elaborate topology vector and the definition of topology vector in Section 3.2, last we illustrate the dynamic weighting strategy to fuse Euclidean distance and topology distance.

3.1 Preliminaries

We note that learning descriptors is the image embedding from image patches to descriptor vectors. Suppose a batch of training data generates the corresponding descriptors \( y = \{A_i, p_i\} \), where \( A = \{a_1, a_2, ..., a_n\} \), \( P = \{p_1, p_2, ..., p_n\} \) and \( n \) is the batch size. Normally descriptor vectors are unit-length and 128-dimensional as SIFT [22] descriptors. Note that \( a_i \) and \( p_j \) are a matching pair if \( i \) equals \( j \) and non-matching pair otherwise.

The triplet loss [33] encourages the distance of negative samples to be larger than that of positive samples, which denote the non-matching pairs and matching pairs respectively in descriptors learning:

\[
L_{\text{triplet}} = \frac{1}{n} \sum_{i=1}^{n} \max(0, \text{margin} + \Gamma^+(a_i, p_i) - \Gamma^-(a_i, p_i)).
\]

HardNet [27] first introduces triplet loss to descriptors learning which tries to minimize the Euclidean distance between matching descriptors and maximize that of nearest non-matching descriptors. In HardNet,

\[
\Gamma^+(a_i, p_i) = d_E(a_i, p_i)
\]

\[
\Gamma^-(a_i, p_i) = \min(d_E(a_i, p_{j\text{min}}), d_E(a_{k\text{min}}, p_i))
\]

where \( d_E \) is the Euclidean distance, \( d_E(a_i, p_{j\text{min}}) \) and \( d_E(a_{k\text{min}}, p_i) \) denote the Euclidean distance of nearest non-matching descriptors. It would be time-consuming to compute the Euclidean distance for a large number of descriptors, fortunately the dot product can be used to calculate Euclidean distance between two descriptors when descriptors are unit-length vector: \( \|a_i\|_2 = 1 \):

\[
d_E(a_i, p_j) = \sqrt{2 - 2a_i^T p_j}
\]

However, we observe that only matching descriptors \( a_i, p_i \) and nearest non-matching descriptor \( p_{j\text{min}} \) or \( a_{k\text{min}} \) are used for CNN’s back-propagation, which leads the inconsistent distribution of descriptors in \( A \) and \( P \), also known as topology difference between \( A \) and \( P \). Actually, descriptors set \( A \) and \( P \) should have similar topology because descriptors in them have a one-to-one matching relationship. In next sections we would illustrate how to reduce topology difference between \( A \) and \( P \).

3.2 Topology Measure

LLE [32] is a common manifold learning algorithm for data dimensionality reduction, which manages the same locally linear topology between high-dimensional data and low-dimensional data. In the view of manifold learning, property of Euclidean space is only retained in a small local region, so LLE fits each data sample by its kNN samples:

\[
x_i = w_{i1}x_{i1} + w_{i2}x_{i2} + ... + w_{ik}x_{ik}
\]

where \( x_{ij}, j = 1, 2, ..., k \) is the kNN samples of \( x_i \) and \( w_{ij} \) is the fitting weights. Followed by LLE, we establish a locally linear topology vector for each descriptor depicting linear topological relationship among descriptor \( a_i \) or \( p_i \) and its kNN descriptors \( a_{ij} \) or \( p_{ij} \).

Here we take descriptors set \( A \) and its elements \( a_i, i = 1, 2, ..., n \) as example, obviously we can solve this for \( P \) by the same steps. As shown in Fig. 2, to solve linear topological relationship between \( a_i \) and its kNN descriptors, we first determine kNN descriptors \( a_{ij} \) for \( a_i \). We compute the Euclidean distance between \( a_i \) and all other descriptors in a mini-batch by Eq. 4, then we sort the distances in ascending order and take the elements corresponding to front \( k \) distances as the kNN descriptors of \( a_i \).

The next step is to linearly fit \( a_i \) using \( a_{ij} \), which can be written as:

\[
a_i = w_{i1}^a a_{i1} + w_{i2}^a a_{i2} + ... + w_{ik}^a a_{ik}
\]

So the optimization goal is:

\[
\arg\min_{w} \|a_i - \sum_{j=1}^{k} w_{ij}^a a_{ij}\|^2
\]

s.t. \( \sum_{j=1}^{k} w_{ij}^a = 1 \)

Now write the above formula in matrix form. Assume \( A_i \in \mathbb{R}^{128 \times k} \) is a matrix by \( a_i \) repeating \( k \) times, and \( N_i^a \in \mathbb{R}^{128 \times k} \) consists of \( a_{ij} \). Now note \( S_i = (A_i - N_i^a)^T (A_i - N_i^a) \), where \( S_i \) is a real symmetric and semi-definite matrix, so the above optimization formula can be written as:

\[
\arg\min_{W_i} \sum_{k} w_{ik}^a S_i W_i^a
\]

s.t. \( W_i^a^T 1_k = 1 \)

This above optimization problem has the closed solution:

\[
W_i^a = \frac{S_i^{-1} 1_k}{1_k^T S_i^{-1} 1_k}
\]

Obviously \( W_i^a = [w_{i1}^a, w_{i2}^a, ..., w_{ik}^a] \in \mathbb{R}^k \) is the weight sequence depicting the linear topological relationship among \( a_i \) and its kNN
descriptors $a_{ij}$. Now we expand $W_i$ to the locally linear topology vector $T_i^a = [t_{i1}^a, t_{i2}^a, \ldots, t_{in}^a] \in \mathbb{R}^n$ by the following principle:

$$t_{ij}^a = \begin{cases} w_{ij}^a, & a_j \in kNN(a_i) \\ 0, & \text{otherwise} \end{cases}$$

(9)

By above equation, $t_{ij}^a$ equals 0 if $a_j$ is not one of $k$NN descriptors of $a_i$. Obviously we can establish the topology vector $T_i^a$ for each $p_i$ in descriptors set $P$ followed by above steps.

$T_i^a$ and $T_i^p$ are the topology vectors of descriptors $a_i$ and $p_i$, which depict the locally linear relationship among $a_i$ or $p_i$ and $a_{ij}$ or $p_{ij}$. The length of $T_i^a$ and $T_i^p$ is not a fixed number, while it equals batch size $n$, an important hyper-parameter of CNN. The topology vectors $T_i^a$ and $T_i^p$ are sparse arrays with $k$ non-zero elements, where $k$ is far less than $n$. Otherwise, sum of all elements in topology vectors equals 1 by Eq. 6.

We could solve a topology vector $T_i^a$ or $T_i^p$ for each descriptor $a_i$ or $p_i$ followed by above steps, then we take the $l_1$ distance between $T_i^a$ and $T_i^p$ as the topology distance between descriptors $a_i$ and $p_i$:

$$d_T(a_i, p_j) = \frac{1}{4} \| T_i^a - T_i^p \|_1$$

(10)

Note that 4 is the maximum value of $\| T_i^a - T_i^p \|_1$, which normalizes the topology distance into the range of 0 to 1. Meanwhile, we choose the $l_1$ distance to measure difference between topology vectors as they are sparse vectors.

The topology distance $d_T(a_i, p_i)$ reflects the neighborhood difference between matching descriptors $a_i$ and $p_i$, while two aspects are required by a small topology distance: $k$NN descriptors of $a_i$ match that of $p_i$ and fitting weights $w_{ij}^a$ are similar with $w_{ij}^p$. We hope the matching descriptors $a_i$ and $p_i$ have the consistent local topology so that global topology difference between $A$ and $P$ is small.

### 3.3 Dynamic Weighting Strategy

In HardNet [27], only the matching descriptors and nearest non-matching descriptors are used for for CNN’s back-propagation, which neglects the topology similarity between descriptor sets $A$ and $P$. In this section we encourage the similar topology between matching descriptors $a_i$ and $p_i$ by minimizing their topology distance $d_T(a_i, p_i)$. So we define the distance of positive samples $\Gamma^+(a_i, p_i)$ in triplet loss as following:

$$\Gamma^+(a_i, p_i) = \lambda d_T(a_i, p_i) + (1 - \lambda)d_T(a_i, p_i)$$

(11)

where weight $\lambda$ is a hyper-parameter in range 0 to 1 to balance the Euclidean distance and topology distance.

By minimizing $\Gamma^+(a_i, p_i)$, first we can reduce Euclidean distance of matching descriptors, and then we encourage $a_i$ and $p_i$ have the matching $k$NN descriptors, last we reduce the difference of topological weights between $a_i$ and $p_i$, while early works [27, 38, 42, 48] only consider the first item. Compared with Hardnet only using matching descriptors and nearest non-matching descriptors to update CNN, our method considers additional $k$NN descriptors of matching descriptors for CNN’s back-propagation.

In Eq. 11, weight $\lambda$ is an important parameter that directly affects the performance of descriptors. We note that the larger $\lambda$ focuses more on the Euclidean distance between descriptors and contributes to the more discriminative descriptors, and a smaller $\lambda$ focuses more on the topology distance between descriptors and contributes to the more robust descriptors. In this paper, we employ the dynamic weighting strategy to fuse the Euclidean distance and topology distance of matching descriptors. Specifically, we choose a larger $\lambda$ in the former training epochs, then we decay the value of $\lambda$ gradually. The value of $\lambda$ in $n$-th iteration can be solved by the following equation:

$$\lambda = \max \{ 1 - \left( \frac{\max(0, n - n_0)}{N} \right) \times r, 0.5 \}$$

(12)

By Eq. 12, $\lambda$ equals 1 in the initial $n_0$ iterations during training, and decays $r$ for each $N$ iterations. The minimum value of $\lambda$ is 0.5, which takes Euclidean distance and topology distance equally.

For the negative samples, non-matching descriptors in triplet loss, we found there is no need to encourage the large topology distance for them because there may exist matching pairs inside $k$NN descriptors of non-matching descriptors. So we define the distance of negative samples as the Euclidean distance of nearest non-matching descriptors like HardNet.

We note that our method have two overwhelming advantages compared with former triplet loss: First, besides the point-to-point distance constraints, our method takes advantage of the high-order topology constraints to improve the robustness of descriptors; Second, our method considers the neighborhood information of positive sample, which means more descriptors are used to update CNN.

### 4 EXPERIMENTS

The main contribution of our work is to propose the topology measure besides Euclidean distance for triplet loss to encourage the similar topology between descriptor sets $A$ and $P$. To verify the generalization of our method, we test our method on the basis of HardNet [27] and CDF [48], where HardNet first introduces triplet loss into learning descriptors and CDF is the state-of-the-art method of learning descriptors using triplet loss.

To validate the performance of our topology consistency descriptor TCDesc, we conduct our experiments in three benchmarks: UBC PhotoTourism [4], HPatches [1] and W1BS dataset [28]. UBC PhotoTourism [4] is currently the largest and the most widely used local image patches matching dataset, which consists of three subsets(Liberty, NotreDame and Yosemite) with more than 400k image patches. HPatches [1] presents the more complicated and more comprehensive three tasks to evaluate descriptors: Patch Verification, Image Matching, and Patch Retrieval. W1BS dataset [28] consists of 40 image pairs and provides more challenging tasks with severe nuisance factors to explore the performance of descriptors in extreme conditions.

#### 4.1 Implementations

We use the same configuration as former works to guarantee the improvement of experimental results attributes to our novel topology measure. We use the CNN architecture proposed in L2-Net [37] with seven convolutional layers and a Local Response Normalization layer. We note that we only train our network on benchmark UBC PhotoTourism and then test other two benchmarks using the trained model. The size of image patches in UBC PhotoTourism is
Table 1: Patch verification performance on the UBC PhotoTourism benchmark. Numbers shown are FPR95(%), while the lower FPR95 indicates the better performance of learned descriptors. Plus “+” denotes training with data augmentation. We test our method on the basis of HardNet [27] and CDF [48], which is noted as TCDesc-HN and TCDesc-CDF respectively.

| Descriptors       | Length | Train | Notredame | Liberty | Yosemite | Notredame | Liberty | Yosemite | Mean |
|-------------------|--------|-------|-----------|---------|----------|-----------|---------|----------|------|
| SIFT [22]         | 128    | Test  | 29.84     | 22.53   | 27.29    | 26.55     |
| DeepDesc [35]     | 128    |       |           |         |          |           |         |          |      |
| L2-Net+ [37]      | 128    |       | 2.36      | 4.70    | 0.72     | 1.29      | 2.51    | 1.71     | 2.23 |
| CS L2-Net+ [37]   | 256    |       | 2.55      | 4.24    | 0.87     | 1.39      | 3.81    | 2.84     | 2.61 |
| HardNet [27]      | 128    |       | 1.47      | 2.67    | 0.62     | 0.88      | 2.14    | 1.65     | 1.57 |
| HardNet+ [27]     | 128    |       | 1.49      | 2.51    | 0.53     | 0.78      | 1.96    | 1.84     | 1.51 |
| DOAP+ [15]        | 128    |       | 1.54      | 2.62    | 0.43     | 0.87      | 2.00    | 1.21     | 1.45 |
| DOAP-ST+ [15, 18] | 128    |       | 1.47      | 2.29    | 0.39     | 0.78      | 1.98    | 1.35     | 1.38 |
| ESE [29]          | 128    |       | 1.14      | 2.16    | 0.42     | 0.73      | 2.18    | 1.51     | 1.36 |
| SOSNet [38]       | 128    |       | 1.25      | 2.84    | 0.58     | 0.87      | 1.95    | 1.25     | 1.46 |
| Exp-TLoss [42]    | 128    |       | 1.16      | 2.01    | 0.47     | 0.67      | 1.32    | 1.10     | 1.12 |
| CDF+ [48]         | 128    |       | 1.21      | 2.01    | 0.39     | 0.68      | 1.51    | 1.29     | 1.18 |
| TCDesc-HN+        | 128    |       | 1.47      | 2.38    | 0.43     | 0.72      | 1.47    | 1.23     | 1.28 |
| TCDesc-CDF+       | 128    |       | 1.18      | 1.99    | 0.34     | 0.65      | 1.26    | 1.08     | 1.08 |

64×64, then we downsample each patch to size of 32×32, which is required by of L2-Net. We conduct data augmentation as CDF [48] to flip or rotate image patches randomly. To accord with HardNet [27] and CDF [48], we set the training batch size to be 1024. We train our network for 250 iterations using Stochastic Gradient Descent(SGD) with momentum 0.9 and weight decay 10⁻⁴, and the learning rate is decayed linearly from 0.1 to 0. We set the number of nearest neighbor descriptors k and the weight to balance Euclidean distance and topology distance λ. Our novel topology measure consider k nearest neighbor descriptors of matching descriptor for CNN’s back-propagation, so the larger k means we use more descriptors to update CNN’s parameters in each iteration. However, by the opinion of maniflod learning, the property of Euclidean space is only retained in a small local region. So it’s not feasible for us to define a very large k. Former works [9, 11, 49] choose the value of k in the range of 10 to 15. We set k in our experiments to be 20 considering the large batch size 1024.

In Section 3.3, we define the distance of positive samples in triplet as the dynamic weighting of Euclidean distance and topology distance of matching descriptors. As shown in Eq. 12, the weight λ is determined by initial steps n₀, decay steps N and decay rate r. In our experiments, we set n₀, N and r as 5×10⁴, 10⁴ and 0.025 respectively. Within the total 250k iterations, the weight λ equals 1.0 in the initial 50k iterations and declines 0.025 for each 10k iterations in the later 200k iterations, which means λ declines from 1.0 to 0.5 during the whole training.

4.2 UBC PhotoTourism benchmark

UBC PhotoTourism [4] is the first large benchmark of learning descriptors from image patches which consists of more than 400k image patches extracted from large 3D reconstruction scenes. UBC PhotoTourism consists of three subsets: Liberty, Notredame and Yosemite. Usually we train one subset and test other two subsets. The false positive rate at 95% recall (FPR95) is employed by UBC PhotoTourism to evaluate the performance of learned descriptors, where the lower FPR95 indicates the better performance.

We test our method on the basis of HardNet [27] and CDF [48], which are the first work introducing triplet loss into learning descriptors and the state-of-the-art method of learning descriptors using triplet loss respectively. Specifically, we modify the distance of positive sample in their triplet losses as the linear weighting of Euclidean distance and topology distance of matching descriptors. Then we compare our method with SIFT [22], DeepDesc [35], L2-Net [37], HardNet [27], DOAP [15], ESE [29], SOSNet [38], Exp-TLoss [42] and CDF [48]. We present the performance of descriptors learned by various algorithms in Table 1.

As can be seen, our novel topology measure improves performance of both descriptors learned by HardNet and CDF. Specifically, mean FPR95 of HardNet declines from 1.51 to 1.28 after introducing our topology measure and that of CDF declines from 1.18 to 1.08. Furthermore, our method reduces the FPR95 of HardNet and CDF on every test task. Otherwise, as presented in Table 1, our TCDesc on the basis of CDF leads the state-of-the-art result with the lowest FPR95 1.08.

The experimental results on UBC PhotoTourism benchmark validate the generalization of our method: we can improve performances of several descriptors learned by former triplet loss.

4.3 HPatches benchmark

HPatches benchmark [1] consists of 116 sequences where the main nuisance factor of 57 sequences is illumination and that of 59 sequences is viewpoint. Feature points in the 3D scenes are detected by DoG, Hessian-Hessian and Harris-Laplace. Then the reference feature points are projected to the target image using the groundtruth homographies to solve the target feature points.

Compared with UBC PhotoTourism benchmark, HPatches benchmark [1] provides more diverse data samples and more sophisticated tasks. HPatches [1] defines three tasks to evaluate descriptors: Patch Verification, Image Matching, and Patch Retrieval, and each task is
Wide baseline stereo matching [39] aims to find correspondences of
with SIFT [22], HardNet [27], DOAP [15], SOSNet [38],
TCDesc-CDF
Liberty
Illumination(L):
difference in direction, intensity and wavelength
Geometry(G):
difference in object appearance caused by season
Appearance(A):
the nuisance factor:
mark [28].

As can be seen in Fig. 3, there only exists a small margin among mAP of various learning-based descriptors in three tasks. In task Patch Verification, our TCDesc-CDF performs a little worse than CDF, and TCDesc-HN performs a little worse than HardNet, which mainly results from the topology difference of descriptors in benchmarks UBC PhotoTourism and HPatches. In task Image Matching, our TCDesc-CDF and TCDesc-HN lead the state-of-the-art results and perform much better than CDF and TCDesc-HN, which proves the effectiveness of our topology consistent descriptors in image matching. In task Patch Retrieval, our TCDesc-CDF and TCDesc-HN both outperform than CDF and TCDesc-HN, and the TCDesc-CDF achieves the highest mAP(70.50) in this task.

4.4 Wide baseline stereo

Wide baseline stereo matching [39] aims to find correspondences of two images in wide baseline setups, i.e., cameras with distant focal centers. So it is more challenging than normal image matching. To verify generalization of our TCDesc and prove its advantages in extreme conditions, we conduct our experiments on WIBS benchmark [28].

WIBS dataset consists of 40 image pairs divided into 5 parts by the nuisance factor:
Appearance(A): difference in object appearance caused by season or weather changes;
Geometry(G): difference in camera positions and scales;
Illumination(L): difference in direction, intensity and wavelength of light sources;

**Table 2: Impact of hyper-parameter k.** The larger k means that we define a larger local region to depict linear topology for descriptors and take more descriptors for CNN’s back-propagation. However, we found that descriptors perform similarly under different values of k.

| parameter | value | train | Liberty |
|-----------|-------|-------|---------|
|           |       | test  | Notredim | Yosemite | Mean |
| k         | 5     | 0.38  | 1.27    | 0.83     |
|          | 10    | 0.37  | 1.21    | 0.79     |
|          | 15    | 0.39  | 1.30    | 0.85     |
|          | 20    | **0.34** | 1.26  | 0.80     |

Sensor(S): difference in sensor type, including visible, IR, MR;
Map to photo: object image and map image.

WIBS dataset uses multi detectors MSER [24], Hessian-Affine [25] and FOCI [51] to detect affine-covariant regions and normalize the regions to size $41 \times 41$. The average recall on ground truth correspondences of image pairs are employed to evaluate the performance of descriptors.

We compare our TCDesc-HN and TCDesc-CDF with SIFT [22], HardNet [27], SOSNet [38], Exp-TLoss [42] and CDF [48], where our descriptors TCDesc-HN and TCDesc-CDF are trained on the basis of HardNet [27] and CDF [48] respectively.

As can be seen in Fig. 3, there only exists a small margin among mAP of various learning-based descriptors in three tasks. In task Patch Verification, our TCDesc-CDF performs a little worse than CDF, and TCDesc-HN performs a little worse than HardNet, which mainly results from the topology difference of descriptors in benchmarks UBC PhotoTourism and HPatches. In task Image Matching, our TCDesc-CDF and TCDesc-HN lead the state-of-the-art results and perform much better than CDF and TCDesc-HN, which proves the effectiveness of our topology consistent descriptors in image matching. In task Patch Retrieval, our TCDesc-CDF and TCDesc-HN both outperform than CDF and TCDesc-HN, and the TCDesc-CDF achieves the highest mAP(70.50) in this task.

5 DISCUSSIONS

In this Section, we explore the impact of hyper-parameters $k$ to our topology consistent descriptors TCDesc-CDF. We first train our models on subset Liberty of UBC PhotoTourism benchmark and test in other two subsets under different values of $k$. The larger $k$ means...
that we define a larger local region to depict linear topology for descriptors and take more descriptors for CNN’s back-propagation. However, we found that descriptors perform similarly under different values of $k$ on UBC PhotoTourism.

We then conduct our experiment on HPatches benchmark. We evaluate the performances of descriptors generated by models in Table 2. As can be seen in Fig 5, the larger $k$ contributes the better performance in task Patch Verification and Patch Retrieval. In task Image Matching, descriptors under $k$ of 10 outperform than descriptors under $k$ of 15, which may result from the worse model with larger FPR95 as presented in Table 2. We conclude that the larger $k$ contributes to the more robust descriptors: descriptors generated by the trained model under large $k$ performs better than that under smaller $k$ on HPatches benchmark, though they perform similarly on UBC PhotoTourism benchmark.

6 CONCLUSIONS

We observe the former triplet loss fails to maintain the similar topology between two descriptor sets since it takes the Euclidean distance between descriptors as the only measure. In this work, we propose a novel topology measure to learn topology consistent descriptors. Inspired by LLE, we first construct a topology vector for each descriptor which depicts the linear topology relationship among descriptor and its $k$NN descriptors. Then we define the topology distance of descriptors as the difference of their topology vector, where the topology distance indicates the neighborhood difference of descriptors. Last we employ the dynamic weighting strategy to fuse the Euclidean distance and topology distance of matching descriptors modify the distance of positive samples of triplet loss as the fusion result. The similar topology between two descriptor sets are encouraged with topology distance of matching descriptors.

Experimental results on several benchmarks validate the generalization of our method since our method can improve performance of several algorithms using triplet loss. Last we discuss the impact of hyper-parameter $k$ and found the larger $k$ contributes the more robust descriptors.

However, our method is not appropriate for learning binary descriptors because the binary descriptor can not be linear fitted by its $k$NN descriptors with float fitting weights. We note that the idea of our method, locally linear topology consistency can be extended to many other fields of image embedding, such as face recognition, person ReID, image retrieval.
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