HyNet: Local Descriptor with Hybrid Similarity Measure and Triplet Loss

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Abstract

Recent works show that local descriptor learning benefits from the use of $L_2$ normalisation, however, an in-depth analysis of this effect lacks in the literature. In this paper, we investigate how $L_2$ normalisation affects the back-propagated descriptor gradients during training. Based on our observations, we propose HyNet, a new local descriptor that leads to state-of-the-art results in matching. HyNet introduces a hybrid similarity measure for triplet margin loss, a regularisation term constraining the descriptor norm, and a new network architecture that performs $L_2$ normalisation of all intermediate feature maps and the output descriptors. HyNet surpasses previous methods by a significant margin on standard benchmarks that include patch matching, verification, and retrieval, as well as outperforming full end-to-end methods on 3D reconstruction tasks.

1 Introduction

Local feature detectors and descriptors play a key role in many computer vision tasks such as 3D reconstruction or visual localisation. Recently, joint detection and description \cite{45, 29, 10, 22, 25, 13} has drawn significant attention. Despite the alluring idea of the end-to-end detection and description, the classic two-stage strategy withstood years of tests in many computer vision tasks and still gives a competitive performance in standard benchmarks \cite{5, 1, 36, 18}. Moreover, customised matchers \cite{27, 34, 33, 4, 35} have also contributed to boosting the matching performance, where the time complexity is critical. Despite the progress in end-to-end methods, the two-stage process still deserves attention since it often leads to competitive results in the overall matching system \cite{41}.

Deep descriptors \cite{38, 2, 40, 26, 19, 15, 41, 47} have shown superiority over hand-crafted ones \cite{23, 44} in different tasks \cite{11, 18, 5, 36}. Current works mainly focus on improving the loss function or the sampling strategy. L2-Net \cite{40} introduces a progressive batch sampling with an N-Pair loss. HardNet \cite{26} uses a simple yet effective hard negative mining strategy, justifying the importance of the sampling. Other than contrastive or triplet loss, DOAP \cite{15} employs a retrieval based ranking loss. GeoDesc \cite{24} integrates geometry constraints from multi-view reconstructions to benefit the training. Besides the first-order optimisation, SOSNet \cite{41} shows that second-order constraints further improve the descriptors.

It has been widely observed that $L_2$ normalisation of the descriptors leads to consistent improvements. Methods such as \cite{40, 26, 15, 41, 49, 47} which $L_2$ normalised descriptors, significantly outperform early unnormalised descriptors \cite{38, 2}. Moreover, even hand-crafted descriptors can be improved with $L_2$ normalisation \cite{11}. All such observations indicate that
descriptors are better distinguished by their vector directions rather than the magnitudes (L_2 norms), where similar conclusions can also be found in other feature embedding tasks [43] [8] [21].

We therefore analyse the impact of L_2 normalisation on learning from the gradients perspective. Since the gradients for each layer are generated via the chain rule [14], we analyse them at the beginning of the chain, where they are generated by the given similarity measure. Our intuition is that the gradient direction should benefit the optimisation of descriptor directions, while the gradient magnitude should be adaptive to the level of hardness of the training samples. Consequently, HyNet is introduced to make better use of the gradient signals in terms of direction and magnitude.

Despite the evolving design of loss function, triplet loss is still employed in state-of-the-art local descriptors [28] [41]. Furthermore, triplet loss has also earned noticeable popularity in various embedding tasks, e.g., face recognition [37] [30] and person re-identification [6] [16]. An interesting observation in [28] indicates that the improvements from the classic contrastive and triplet loss are marginal. In this work, we further show that state-of-the-art local descriptor can be learned by triplet loss with a better designed similarity measure.

Specifically, we propose: 1) a hybrid similarity measure that can balance the gradient contributions from positive and negative samples, 2) a regularisation term which provides suitable constraints on descriptor norms, and 3) a new network architecture that is able to L_2 normalise the intermediate feature maps.

2 Gradient Analysis

In this section, we explore how the widely used inner product and L_2 distance provide gradients for training normalised and unnormalised descriptors.

2.1 Preliminaries

We denote \( \mathcal{L}(s(x, y)) \) as the loss for a descriptor pair \((x, y)\), where \( s(\cdot, \cdot) \) is a similarity measure. Whether \((x, y)\) are positive (matching) or negative (non-matching), the gradients with respect to the descriptors are calculated as:

\[
\frac{\partial \mathcal{L}}{\partial x} = \frac{\partial \mathcal{L}}{\partial s} \frac{\partial s}{\partial x}, \quad \frac{\partial \mathcal{L}}{\partial y} = \frac{\partial \mathcal{L}}{\partial s} \frac{\partial s}{\partial y},
\]

where \((x, y)\) are omitted for clarity. Importantly, the gradients for learnable weights of a network are derived in Eqn.(1) at the beginning of the chain, and play a key role during training. Note that \( \frac{\partial \mathcal{L}}{\partial s} \) is a scalar, while the direction of the gradient is determined by the partial derivatives of \( s \). We consider the two most commonly used similarity measures, namely inner product and L_2 distance, for descriptors with and without L_2 normalisation:

\[
s_I = x^T y, \quad s_I = \frac{x^T y}{\|x\| \|y\|}, \quad s_L = \|x - y\|, \quad s_L = \frac{x}{\|x\|} - \frac{y}{\|y\|},
\]

where \( \| \cdot \| \) denotes the L_2 norm (\( \|x\| = \sqrt{\sum x_i^2} \)). \( s_I \) and \( s_L \) are similarity measures\(^1\) for normalised descriptors while \( s_I \) and \( s_L \) are for the unnormalised ones. Note that we consider L_2 normalisation as a part of the similarity measure. We then obtain the partial derivatives:

\[
\frac{\partial s_I}{\partial x} = y, \quad \frac{\partial s_I}{\partial y} = x, \quad \frac{\partial s_L}{\partial x} = \frac{1}{s_L} (x - y), \quad \frac{\partial s_L}{\partial y} = \frac{1}{s_L} (y - x),
\]

\[
\frac{\partial s_I}{\partial x} = \frac{1}{\|x\| \|y\|} (x - y) \frac{x^T y}{\|x\|^2}, \quad \frac{\partial s_I}{\partial y} = \frac{1}{\|x\| \|y\|} (y - x) \frac{x^T y}{\|y\|^2}, \quad \frac{\partial s_L}{\partial x} = \frac{1}{s_L} \frac{x^T y}{\|x\|^2}, \quad \frac{\partial s_L}{\partial y} = \frac{1}{s_L} \frac{x^T y}{\|y\|^2} (y - x).
\]

In the following sections we analyse the above gradients in terms of directions and magnitudes.

\(^1\)To ensure consistency, we refer to the L_2 distance also as a similarity measure even though it measures the inverse similarity.
2.2 Gradient Direction

Optimal gradient direction is the key for convergence, i.e., a learning process will not converge given incorrectly directed gradients, regardless of the learning rate. We denote $\Delta = \Delta_\parallel + \Delta_\perp$, where $\Delta$ is the gradient direction, $\Delta_\parallel$ and $\Delta_\perp$ are the parallel and orthogonal components, respectively. According to Eqn. (3), we obtain $|\Delta_\parallel| = x^T \frac{\partial \Delta}{\partial x} = 0$, and similarly for $y^T \frac{\partial \Delta}{\partial y} = 0$, i.e., gradients are always orthogonal to the descriptors, indicating that L2 normalised descriptors only have $\Delta_\perp$. Meanwhile, unnormalised descriptors both components non-zero. For better understanding, we illustrate 2D descriptors and the corresponding gradient descent directions (negative gradient direction) in Fig. 1, where $\theta$ is the angle between descriptors. Specifically, $\Delta_\parallel$ modifies the descriptor magnitude (L2 norms), while $\Delta_\perp$ updates the descriptor direction. However, since descriptor magnitudes can be harmful for matching (see Sec. 1), the training should focus on the optimisation of the descriptor directions, which can be achieved with L2 normalised descriptors. An interesting question is whether it is possible to make a better use of $\Delta_\parallel$. We address this problem in Sec. 3.1 and show that detailed analysis leads to training constraints that improve the performance.

2.3 Gradient Magnitude

The training gradients should have not only the optimal directions but also the properly scaled magnitudes. The magnitude should be adapted to the level of 'hardness' of the training samples, i.e., hard samples should receive a stronger update over easy ones.

We focus on L2 normalised descriptors whose gradients have optimal directions. We denote $u = \frac{x}{||x||}$ and $v = \frac{y}{||y||}$ as two descriptors normalised with L2. With a slight abuse of notation, we use $s(\theta)$ and $g(\theta)$ to represent the similarity measure and gradient magnitude, respectively, with angle $\theta$ between $u$ and $v$:

$$
\begin{align*}
  s_I(\theta) &= u^T v = \cos \theta, \\
  g_I(\theta) &= |\frac{d}{d\theta} u^T v| = |\sin \theta|, \\
  s_L(\theta) &= ||u - v|| = \sqrt{2(1 - \cos \theta)}, \\
  g_L(\theta) &= |\frac{d}{d\theta} ||u - v||| = |\frac{\sin \theta}{\sqrt{2(1 - \cos \theta)}}|,
\end{align*}
$$

where $\theta = \arccos u^T v$, and $|\cdot|$ denotes the absolute value.
We analyse the similarities and gradient magnitudes from Eqn. (4) in the real descriptor space during training. Fig. 2(a) shows the distribution of $\theta$ from 512K descriptor pairs, where the number of positive and negative pairs is 50% each. Specifically, following the hard negative mining strategy of [26], we sample 512 triplets (one positive pair and one negative) from each of the 1K randomly constructed batches of size 1024. Fig. 2(a) shows the $\theta$ distribution of HardNet and SOSNet in training, i.e., both models are trained and tested on Liberty. As shown, almost all hard negatives and positives have $\theta$ in the range $[0, \pi/2]$. Worth noting that easy negatives may have $\theta > \pi/2$, however, sampling hard negatives only, has been proven to be effective [26]. Similarly, we observe how $g_I(\theta)$ and $g_L(\theta)$ behave in range $[0, \pi/2]$, which is highlighted in Fig. 2(b). The gradients differ, i.e., $g_I(\theta)$ is monotonically increasing while $g_L(\theta)$ is decreasing. It indicates that $g_I(\theta)$ is more beneficial for the optimisation of positives, since hard positives (large $\theta \to \pi/2$), generate large gradients compared to easy positives (small $\theta$). In contrast, $g_L(\theta)$ favours negatives, as hard negatives (small $\theta$) generate large updates compared to the easy negatives (large $\theta$). These observations lead to the conclusion that neither the inner product nor the L$^2$ on its own can balance the optimisation with positives and negatives.

It is also worth noting that according to Eqn. (1), the overall gradient magnitude is further weighted by $\frac{\partial L}{\partial s}$, which means a better form of $L$ may alleviate the inherent flaws of $g_I(\theta)$ and $g_L(\theta)$. Consequently, in Sec. 3.2 we show that a carefully designed similarity measure leads to the state-of-the-art performance with the standard triplet loss.

3 Method

Building upon the analysis from the previous section, we propose to improve the descriptor learning by 1) introducing a regularisation term that provides a beneficial $\Delta \|$, 2) a hybrid similarity measure that can strike a balance between the contribution of positives and negatives to the gradient update, 3) a new network architecture that normalises the intermediate feature maps with affine L$^2$ such that they are optimised in their directions rather than the magnitudes.

3.1 L$^2$ Norm Regularisation

Section 2.2 shows that L$^2$ normalisation excludes parallel gradients $\Delta \|$, i.e., there are no constraints on the descriptor norms which can vary with scaling of image intensities. Intuitively, a possible way of making positive contributions from $\Delta \|$ to the optimisation is to introduce the following constraint before the L$^2$ normalisation:

$$R_{L^2} = \frac{1}{N} \sum_{i=1}^{N} (\|x_i\| - \|x_i^+\|)^2.$$  (5)

where $x_i$ and $x_i^+$ are a positive pair of descriptors before L$^2$ normalisation. As a regularisation term, $R_{L^2}$ drives the network to be robust to image intensity changes, e.g., caused by different illuminations.

3.2 Hybrid Similarity Measure and Triplet Loss

The standard triplet loss is defined as:

$$L_{Triplet} = \frac{1}{N} \sum_{i=1}^{N} \max(0, m + s(\theta_i^+) - s(\theta_i^-)),$$  (6)

where $m$ is the margin. $\theta_i^+$ and $\theta_i^-$ are the angles for the positive and negative pairs of the $i$-th descriptor triplet, i.e., the angles between the anchor descriptor and its positive and negative samples.

Remarkable improvements have been made by modifying the standard triplet loss [26, 46, 48, 12, 48]. From the gradient perspective, when the margin constraint in Eqn. (6) is not satisfied, we obtain $\frac{\partial L_{Triplet}}{\partial s(\theta_i^+)} = 1$, otherwise 0. Hence, according to Eqn. (4), $\frac{\partial s(\theta_i^+)}{\partial \theta_i}$
Figure 3: HyNet architecture. It consists of 7 convolutional layers which all but the last are followed by a FRN [39] normalisation and a TLU non-linearity [39].

and \( \frac{\partial s_i(\theta^{-})}{\partial \theta} \) is directly related to the gradient magnitude. As discussed in Sec. 2.3, \( s_I \) and \( s_L \) lead to significantly different updates from the positive and negative examples. Intuitively, a direct solution would be to use \( s_I \) for positives while \( s_L \) for negatives, however, as we show in Sec. 5 this strategy is not optimal. Instead, we propose a hybrid similarity measure that combines the inner product \( s_I \) and the L\( _2 \) norm:

\[
s_H(\theta) = \frac{1}{Z}[\alpha(1 - s_I(\theta)) + s_L(\theta)],
\]

where \( \alpha \) is a scalar ranging from 0 to +\( \infty \), and \( Z \) is the normalising factor ensuring the gradient has the maximum magnitude of 1.

Finally, our overall loss function is defined as:

\[
L_{Triplet} = \frac{1}{N} \sum_{i=1}^{N} \max(0, m + s_H(\theta^+_i) - s_H(\theta^-_i)) + \gamma R_{L_2}
\]

with \( \gamma \) as a regularisation parameter and \( \alpha \) balancing the contributions from \( s_I \) and \( s_L \). Optimal \( \alpha \) can be found by a grid search which is discussed in Sec. 5.

3.3 Network Architecture

Our intuition for designing the network architecture is based on the analysis in Sec. 2.2 that, similarly to the output descriptors, L\( _2 \) normalisation needs to be applied to the intermediate feature maps. However, we found that additional affine scaling of normalised maps has a positive effect on the output descriptors. To this end, we apply the Filter Response Normalisation (FRN) [39], which has recently been proposed and shown promising results in the classification task. Specifically, FRN normalises each layer of feature maps by:

\[
\hat{f}_i = \gamma \sqrt{N} \frac{f_i}{\|f_i\|} + \beta,
\]

where \( \gamma \) and \( \beta \) are learned parameters, \( f_i \) is the flattened feature map of the \( i \)-th channel and \( N \) is the number of pixels. As argued in [39] the gradients w.r.t \( f_i \) are always orthogonal, hence as discussed in Sec. 2.2 the training can focus on optimising the directions of feature vectors.

Our HyNet architecture is based on L2-Net [40], which consists of seven convolutional layers and outputs 128-dimensional descriptors. As shown in Fig 3, all Batch Normalisation (BN) [17] layers, except the last one before the final L\( _2 \) normalisation in the original L2-Net, are replaced with FRN layers. Moreover, as recommended in [39], each FRN is followed by the Thresholded Linear Unit (TLU) instead of the conventional ReLU. Thus, HyNet has the same number of convolutional weights as HardNet [26] and SOSNet [41].

4 Experiment

Our novel architecture and training is implemented in PyTorch [31]. The network is trained for 200 epochs with a batch size of 1024 and Adam optimizer [20]. Training starts from scratch, and the threshold \( \tau \) in TLU for each layer is initialised with \(-1\). We set \( \alpha = 2 \) and \( \gamma = 0.1 \). In the following experiments, HyNet is compared with recent deep local descriptors [2, 40, 26, 41] as well as end-to-end methods [9, 10, 32] on three standard benchmarks [5, 1, 36].
4.1 UBC

UBC dataset [5] consists of three subsets-scenes, namely Liberty, Notre Dame, and Yosemite. The benchmark is focused on the patch pair verification task, i.e., whether the match is positive or negative. Following the evaluation protocol [5], models are trained on one subset and tested on the other two. In Table 1 we report the standard measure of false positive rate at 95% recall (FPR@95) [5] on six train and test splits. We can observe that, while the performance is nearly saturated, HyNet still shows remarkable improvements over previous methods.

| Train | ND | YOS | LIB | YOS | LIB | YOS | Mean |
|-------|----|-----|-----|-----|-----|-----|------|
| SIFT  | 29.84 | 22.53 | 27.29 | 26.55 | |
| TFeat | 7.39 | 10.13 | 3.06 | 3.80 | 8.06 | 7.24 | 6.64 |
| L2-Net | 2.36 | 4.70 | 0.72 | 1.29 | 2.57 | 1.71 | 2.23 |
| HardNet | 1.49 | 2.51 | 0.53 | 0.78 | 1.96 | 1.84 | 1.51 |
| DOAP | 1.54 | 2.62 | 0.43 | 0.87 | 2.00 | 1.21 | 1.45 |
| SOSNet | 1.08 | 2.12 | 0.35 | 0.67 | 1.03 | 0.95 | 1.03 |
| HyNet | 0.89 | 1.37 | 0.34 | 0.61 | 0.88 | 0.96 | 0.84 |

Table 1: Patch verification performance on the UBC phototour dataset. Numbers denote false positive rates at 95% recall (FPR@95). ND: Notre Dame, LIB: Liberty, YOS: Yosemite.

4.2 HPatches

HPatches dataset [1] evaluates three tasks: patch verification, patch retrieval, and image matching for viewpoint and illumination changes between local patches. Based on different levels of geometric noise, the results are divided into 3 groups: easy, hard, and tough. We show the results in Fig. 4, where all models are trained on Liberty, which is the protocol proposed in [1]. HyNet improves the MAP from the previous state-of-the-art SOSNet [41] by a large margin, i.e., 0.89%, 2.35%, and 1.75% for the three tasks. Note that the improvement of SOSNet over its predecessor HardNet [26] was 0.03%, 0.96%, and 1.14% at the time of its publication.

Figure 4: Results on test set ‘a’ of HPatches [1]. HyNet outperforms the state-of-the-art SOSNet [41] and other local image descriptors in all metrics on this benchmark.

4.3 ETH

ETH SfM benchmark [36] evaluates local descriptors in the task of Structure from Motion (SfM) for outdoor scenes. To quantify the SfM quality, in Table 2 we follow the protocol from [36] and report the number of registered images, reconstructed sparse and dense points, mean track length, and mean reprojection error. First, we compare HyNet with HardNet [26] and SOSNet [41] by using the same local patches extracted from DoG detector, which is presented above the dashed lines. Since the detector is fixed, the results reflect the performance of the descriptors. To ensure a fair comparison, HardNet, SOSNet, and HyNet are all trained on Liberty from UBC dataset [5]. In this benchmark, HyNet exhibits significant superiority by registering more images for large scenes and reconstructing more sparse points, while the results for the other metrics are on par with top performing descriptors. Next, we compare HyNet to the recent end-to-end methods, namely SuperPoint [9], D2-Net [10] and R2D2 [32]. DoG+HyNet shows significantly better performance on larger scenes, for example, Madrid Metropolis and Gendarmenmarkt, where it gives over 50% more of reconstructed sparse points in 3D. Note that in the SfM task, the number of registered images and reconstructed points is crucial for the quality of 3D models. Moreover, results also show that HyNet generalises.
well to different patches provided by the state-of-the-art detector Key.Net [3], where the average track length is increased for a number of scenes.

| Image       | #Reg. Images | #Sparse Points | #Dense Points | Track Length | Reproj. Error |
|-------------|--------------|----------------|---------------|--------------|---------------|
| Herzjesu    | SIFT (11.3K) | 8              | 7.5K          | 2.18M        | 6.04          |
|             | DoG+HardNet  | 8              | 8.7K          | 2.17M        | 6.04          |
|             | DoG+SOSNet   | 8              | 8.7K          | 2.18M        | 6.04          |
|             | DoG+HyNet    | 8              | 8.9K          | 2.18M        | 6.04          |
|             | SuperPoint (6.1K) | 8 | 5K | 2.18M | 6.04 |
|             | D2-Net (13.1K) | 8 | 13K | 2.18M | 6.04 |
|             | R2D2 (12.1K) | 8              | 10K           | 2.18M        | 6.04          |
|             | Key.Net+HyNet (11.9K) | 8 | 9.4K | 2.18M | 6.04 |
| Fountain    | SIFT (11.3K) | 11             | 14.7K         | 2.18M        | 6.04          |
|             | DoG+HardNet  | 11             | 16.3K         | 2.18M        | 6.04          |
|             | DoG+SOSNet   | 11             | 16.3K         | 2.18M        | 6.04          |
|             | DoG+HyNet    | 11             | 16.5K         | 2.18M        | 6.04          |
|             | SuperPoint (5.5K) | 11 | 7K | 2.18M | 6.04 |
|             | D2-Net (12.5K) | 11 | 19K | 2.18M | 6.04 |
|             | R2D2 (12.6K) | 11             | 13.4K         | 2.18M        | 6.04          |
|             | Key.Net+HyNet (11.9K) | 11 | 12.0K | 2.18M | 6.04 |
| South       | SIFT (13.3K) | 128            | 108K          | 2.18M        | 6.04          |
|             | DoG+HardNet  | 128            | 159K          | 2.18M        | 6.04          |
|             | DoG+SOSNet   | 128            | 160K          | 2.18M        | 6.04          |
|             | DoG+HyNet    | 128            | 166K          | 2.18M        | 6.04          |
|             | SuperPoint (10.6K) | 128 | 125K | 2.18M | 6.04 |
|             | D2-Net (12.4K) | 128 | 178K | 2.18M | 6.04 |
|             | R2D2 (13.2K) | 128            | 136K          | 2.18M        | 6.04          |
|             | Key.Net+HyNet (12.9K) | 128 | 100K | 2.18M | 6.04 |
| Madrid      | SIFT (7.4K)  | 500            | 116K          | 2.18M        | 6.04          |
|             | DoG+HardNet  | 600            | 261K          | 2.18M        | 6.04          |
|             | DoG+SOSNet   | 675            | 240K          | 2.18M        | 6.04          |
|             | DoG+HyNet    | 697            | 337K          | 2.18M        | 6.04          |
|             | SuperPoint (2.1K) | 702 | 125K | 2.18M | 6.04 |
|             | D2-Net (7.74K) | 787 | 229K | 2.18M | 6.04 |
|             | R2D2 (12.9K) | 790            | 158K          | 2.18M        | 6.04          |
|             | Key.Net+HyNet (9.3K) | 897 | 386K | 2.18M | 6.04 |
| Gendarmenmarkt | SIFT (8.5K)  | 1095           | 338K          | 2.18M        | 6.04          |
|             | DoG+HardNet  | 1018           | 827K          | 2.18M        | 6.04          |
|             | DoG+SOSNet   | 1129           | 729K          | 2.18M        | 6.04          |
|             | DoG+HyNet    | 1181           | 927K          | 2.18M        | 6.04          |
|             | SuperPoint (2.3K) | 1112 | 236K | 2.18M | 6.04 |
|             | D2-Net (8.0K) | 1225          | 541K          | 2.18M        | 6.04          |
|             | R2D2 (13.4K) | 1226           | 529K          | 2.18M        | 6.04          |
|             | Key.Net+HyNet (10.6K) | 1259 | 897K | 2.18M | 6.04 |

Table 2: Evaluation results on ETH dataset [36] for SfM. The improvement is in the number of registered images and sparse points, for large scenes in particular.

5 Discussion

In this section, we first investigate how each building block of HyNet contributes to the overall performance, then observe the impact of hyperparameters, and finally, we show the advantage of the proposed hybrid similarity measure over other possible solutions.

Ablation Study is presented in Table 3, which shows how the $L_2$ norm regularisation term $R_{L_2}$, similarity measure and feature map normalisation affect the performance. Specifically, we train different models on Liberty [5] and report average MAP on Hpatches [1] matching task. First, we can see that $R_{L_2}$ helps to boost the performance, justifying our intuition that it optimises the network to be robust to illumination changes. Next, we experiment with different similarities for Eqn. (8), where the best results (through grid search for optimal margin) for each similarity are reported. As shown, $s_H$ improves from $s_I$ and $s_L$ by 1.87% and 0.78% respectively, indicating its effectiveness in balancing the gradient magnitude obtained from the positive and negative samples. Finally, Filter Response Normalisation (FRN) [39] is compared to Batch Normalisation (BN) [17] and Instance Normalisation(IN) [42], where the network with BN is commonly

| Target      | Choice | Other components | MAP  |
|-------------|--------|------------------|------|
| $R_{L_2}$   |        |                  | 53.58|
|             | $\checkmark$ | FRN, $s_H$      | 53.97|
| Similarity measure | $s_L$ | FRN, $\checkmark$ | $R_{L_2}$ | 52.10|
|             | $s_I$  | FRN, $\checkmark$ | $R_{L_2}$ | 53.19|
|             | $s_H$  | FRN, $\checkmark$ | $R_{L_2}$ | 53.97|
| Norm type   | BN     | $s_H$, $\checkmark$ | $R_{L_2}$ | 52.94|
|             | $s_H$  | FRN, $\checkmark$ | $R_{L_2}$ | 52.47|
|             | FRN    | $s_H$, $\checkmark$ | $R_{L_2}$ | 53.97|

Table 3: Ablation of HyNet’s components.
We have introduced a new deep local descriptor named HyNet, which is inspired by the analysis and optimisation of the descriptor gradients. HyNet further benefits from a regularisation term that constrains the descriptor magnitude before L2 normalisation, a hybrid similarity measure that makes different contributions from positive and negative pairs, and a new network architecture which L2 normalises the intermediate feature maps. Empirically, HyNet outperforms previous methods by a significant margin on various tasks. Moreover, a comprehensive ablation study is conducted revealing the contribution of each proposed component on its final performance.

6 Conclusion

Figure 5: (a) Effect of parameter \( \alpha \) in the proposed hybrid loss. We give the matching MAP on HPatches \([1]\) for different \( \alpha \) and margin \( m \) from Eqn. (7) and (8). (b) Gradient magnitude of the proposed HyNet loss for different \( \alpha \). (c) Comparison of the proposed loss to other variants that combine the inner product and L2 loss.

Other possible solutions for using different metrics for the positives and negatives include:

\[
\mathcal{L}_A = \frac{1}{N} \sum_{i=1}^{N} \max(0, m_{L,L} + s_I(\theta^+_i) - s_L(\theta^-_i)),
\]

\[
\mathcal{L}_B = \frac{\alpha}{N} \sum_{i=1}^{N} \max(0, m_I + s_I(\theta^+_i) - s_I(\theta^-_i)) + \frac{1}{N} \sum_{i=1}^{N} \max(0, m_L + s_L(\theta^+_i) - s_L(\theta^-_i)).
\]
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A Appendix

A.1 Image Matching Challenge 2020

We further evaluate HyNet on the newly proposed Image Matching Challenge (IMC) dataset [18]. It consists of two tasks, namely wide-baseline stereo and multi-view reconstruction. Since the ground truth for the test set is not released, we report the performance on the validation set. For fair comparison, we use Key.Net [3] as the detector and compare HyNet with two other state-of-the-art descriptors, HardNet [26] and SOSNet [41]. The evaluation protocol is with a maximum of 2048 keypoints per image and standard descriptor size (512 bytes). We use DEGENSAC [7] for geometric verification, and nearest-neighbour matcher with first-to-second nearest-neighbour ratio test for filtering false-positive matches. Please refer to [18] for exact details of the challenge’s settings.

|            | Stereo | Multi-View | Average |
|------------|--------|------------|---------|
| HardNet    | 63.40  | 74.41      | 68.91   |
| SOSNet     | 63.41  | 74.51      | 68.96   |
| HyNet      | 64.07  | 74.84      | 69.46   |

Table 4: Mean Average Accuracy (mAA) at 10° on IMC dataset [18].

As can be seen from Table 4, HyNet surpasses the previous state-of-the-art methods HardNet and SOSNet on both tasks, which further validates its effectiveness.

A.2 Integrating HyNet with SOSR

In this section, we test HyNet by combining it with the Second Order Similarity Regularisation (SOSR) proposed in [41], results are shown in Table 5 and Fig. 6. As shown, HyNet generalises well with the extra supervision signal from SOSR, indicating its potential of being further boosted by other third-party loss terms.

| Train | ND | YOS | LIB | YOS | LIB | ND | YOS | Mean |
|-------|----|-----|-----|-----|-----|----|-----|------|
| SIFT  | 29.84 | 22.53 | 27.29 | 26.55 |
| HardNet | 1.49 | 2.51 | 0.53 | 0.78 | 1.96 | 1.84 | 1.51 |
| SOSNet | 1.08 | 2.12 | 0.35 | 0.67 | 1.03 | 0.95 | 1.03 |
| HyNet | 0.89 | 1.37 | 0.34 | 0.61 | 0.88 | 0.96 | 0.84 |
| HyNet+SOSR | 0.91 | 1.62 | 0.31 | 0.54 | 0.78 | 0.73 | 0.82 |

Table 5: Patch verification performance on the UBC phototour dataset. Numbers denote false positive rates at 95% recall (FPR@95). ND: Notredame, LIB: Liberty, YOS: Yosemite.

Figure 6: Results on test set ‘a’ of HPatches [1]. Colour of the marker indicates EASY, HARD, and TOUGH noise. The type of marker corresponds to the variants of the experimental settings.

*https://vision.uvic.ca/image-matching-challenge/benchmark/*