PN-Net: Conjoined Triple Deep Network for Learning Local Image Descriptors

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Abstract

In this paper we propose a new approach for learning local descriptors for matching image patches. It has recently been demonstrated that descriptors based on convolutional neural networks (CNN) can significantly improve the matching performance. Unfortunately their computational complexity is prohibitive for any practical application. We address this problem and propose a CNN based descriptor with improved matching performance, significantly reduced training and execution time, as well as low dimensionality. We propose to train the network with triplets of patches that include a positive and negative pairs. To that end we introduce a new loss function that exploits the relations within the triplets. We compare our approach to recently introduced MatchNet and DeepCompare and demonstrate the advantages of our descriptor in terms of performance, memory footprint and speed i.e. when run in GPU, the extraction time of our 128 dimensional feature is comparable to the fastest available binary descriptors such as BRIEF and ORB.

1. Introduction

Finding correspondences between images via local descriptors is one of the most extensively studied problems in computer vision due to the wide range of applications. The field has witnessed several breakthroughs in this area such as SIFT [15], invariant region detectors [18], fast binary descriptors [4], optimised descriptor parameters [23, 21] which have made a significant and wide impact in various computer vision tasks. Recently end-to-end learnt descriptors [9, 20, 25, 11] based on CNN architectures were demonstrated to significantly outperform state of the art features. This was a natural adoption of CNN to local descriptors as deep learning had already been shown to significantly improve in many computer vision areas [14]. However, the performance improvements with CNN based descriptors come at the cost in terms of extensive training time, computation, size of the annotated data as well as significantly larger dimensionality of the feature vector. For example, days of training with GPU on 100s of thousands of training patches are reported in [9, 20, 25, 11], and descriptor dimensionality reaches up to 4096. Moreover, slow execution time i.e. descriptor extraction, even using GPUs, negatively outweighs the benefits of improved matching. Even though the efficiency and dimensionality is improving with new methods, it is still far off descriptors such as BRIEF i.e. 8 bytes, 3μs per descriptor.

Another issue in the area of matching patches is the limited benchmark data. Typically used Oxford data [17] was designed a decade ago and can be considered very small for today’s standards. Also, its original evaluation protocol included detection of interest points which currently are less often used in the evaluations. Hence, different protocols and evaluation measures are adopted in various papers which make a comparative study inaccurate. Patch data from [16] with well defined groundtruth is more convenient to use but the reported error has decreased significantly over past years such that the margin for improvement is very small. Furthermore the training and testing is done on the data from similar distribution and over-fitting may occur.

In this paper we propose a CNN based descriptor that improves the performance of recent methods, reduces matching error from 26% (SIFT) to ≈ 7%, it is of the same dimensionality as SIFT, its extraction time is 40 times faster than SIFT and only 3 times slower than BRIEF, and single epoch training time is 2min. We propose to train the network with Positive and Negative pairs formed by triplets of patches, hence our network is termed PN-Net. We introduce a new loss function, which we call SoftPN, to simul-
taneously exploit the constraints given by the positive and negative pairs. We compare our network and the loss function to other CNN based approaches and demonstrate the improvements. We extend the Oxford data with new image sequences and modify the evaluation protocol such that the data can be used in a similar way to the one from [23], yet it preserves the advantages of having the various type of noise separated for more detailed analysis of descriptors. Together with the patch data it allows to test the generalisation properties of the evaluated methods. We perform extensive evaluation and comparison to the state of the art descriptors and demonstrate the improvements in matching performance, extraction efficiency, dimensionality, and training time.

2. Related work

The design and implementation of local descriptors has undergone a remarkable evolution over the past two decades ranging from differential or moment invariants, correlations, histograms of gradients or other measurements, PCA projected patches etc. An overview of pre-2005 descriptors with SIFT [15] identified as the top performer can be found in [17]. Its benchmark data accelerated the progress in this field and there have been a number of notable contributions, including recent DSP-SIFT [7], falling into the same category of descriptors as SIFT but the improvements were not sufficient to replace SIFT in various applications. The research focus shifted to improve the speed and memory footprint e.g. as in BRIEF [4] and the follow up efforts. Introduction of datasets with correspondence ground truth [23] stimulated development of learning based descriptors which try to optimise descriptor parameters and learn projections or distance metrics [16, 24] for better matching.

End-to-end learning of patch descriptors using CNN has been attempted in several works [9, 25, 20, 11] and consistent improvements were reported over the state of the art descriptors. It was shown in [9] that the features from the last layer of a convolutional deep network trained on ImageNet [19] can outperform SIFT. Furthermore, training a siamese deep network with hinge loss in [25, 20, 11] (two CNN’s sharing the same weights) based on positive and negative patch pairs, resulted in significant improvements in matching performance. Explicit metric learning is often performed in such descriptors to classify similar and dissimilar pairs. This may lead to sub-optimal performance if such learnt representation is used as a descriptor for a different task.

It is well known that careful selection of training data may lead to significant performance increase. Inspired by relevant methods in SVM based classifiers [8], the approach from [20] proposes to improve learning by mining and retraining the network with hard training examples. Many similar ideas can be found in the area of distance metric learning [1] which also exploits various methods of sampling data points to train better projections. In particular Linear Discriminant Embedding, Marginal Fisher Analysis, Neighbourhood Component Analysis or Large Margin Nearest Neighbour focus on exploiting nearest neighbours in training examples and their relations rather than treating all data points equally. A notable example in the context of local descriptors is the nearest neighbour ratio [15] used for matching instead of the absolute Euclidean distance. Similarly, bootstrapping techniques often rely on identifying false positives and false negatives and improve classifiers by re-training on those. The idea of guiding the learning process simultaneously by positive and negative constraints was successful exploited in PN-Learning [13] in patch based online learnt object detector.

We build on the top of these results and propose PN-Net that exploits the positive and negative relations within triplets of training examples in contrast to pairs in siamese networks. A similar idea was recently investigated in the context of image categorisation into 10 object classes, but the reported improvements were marginal [12]. Our triplet network structure and the loss function is different and a patch can be considered as an independent object class, thus the typical matching problem includes 1000s of such classes. We also design a new loss function termed SoftPN, which is inspired by SoftMax ratio and hard negative mining from [20]. As we demonstrate in the experiments our method leads to significant improvements in terms of matching performance, dimensionality, and both training and test speed.

3. PN-Net

In this section, we present our feature descriptor learning method, and we give a brief analysis of its strengths against the previously used CNN architectures and loss functions.

3.1. Overview of the network architecture

Our goal is to compute a representation vector \( D(p) \in \mathbb{R}^d \) of image patch \( p \in \mathbb{R}^{N \times N} \). Descriptor vector \( D(p) \) results from the final layer of a convolutional neural network where the layer size matches the feature dimensionality. In contrast to [11] or [25], which include metric learning, our goal is to generate descriptors that can be used in traditional matching setup i.e. with the \( L_2 \) distance. This has the advantage of opening the application range to various well-studied techniques such as KD-Trees or approximate nearest neighbour search.

Previous work on deep learning of feature descriptors has been based on the siamese networks as illustrated in Figure 1 (top). Such networks consist of two CNNs which accept two parallel inputs and share parameters across networks. The loss function is optimised based on the output of the two networks according to their distinct inputs. A
single distance between a pair of patches is considered for every training example. This architecture is used to extract descriptors showing state-of-the art matching performance in [20, 25].

Architectures exploiting three parallel inputs have recently been investigated in [22] and [12] in the context of ranking and classification. Their loss function makes use of a triplet of images where two images are from the same class, and one is from a different class. Inspired by these techniques we propose an approach to learning local feature descriptors for matching patches. We make use of a triplet of patches where two of them are positive patches from two views of the same point in the 3D space, and the third one is a negative patch extracted from a different point in space. The loss function is then based on three distances considered simultaneously for every training example formed from the triplet. The proposed network is shown in Figure 1(bottom). Examples of the positive and negative training pairs used in previous works as well triplets exploited in our network are shown in Figure 2.

3.2. Conjoined deep network loss functions

In this section we first discuss the Hinge Embedding loss [10] commonly used in conjoined deep network architectures and then we introduce our new loss function that is used in the optimization of the proposed PN-Net triplet based architecture.

3.2.1 Hinge Embedding Loss

The recent works related to deep learning of feature descriptors utilize patch pairs and the Hinge Embedding, [10, 20, 25, 22]. Hinge Embedding criterion was also used with triplets of data points to learn pose descriptors for 3D objects [24].

Let $P = \{p_L, p_R\}$ denote a patch pair and $L \in \{-1, 1\}$ a label indicating negative and positive pairs respectively. Hinge Embedding loss is then computed

$$l(P) = \begin{cases} 
\Delta = ||D(p_L) - D(p_R)||_2 & \text{if } L = 1 \\
\max(0, \mu - ||D(p_L) - D(p_R)||_2) & \text{if } L = -1 
\end{cases}$$

Intuitively the hinge embedding loss penalizes positive pairs that have large distance and negative pairs that have small distance (less than $\mu$).

However as observed in [20], the majority of the negative patch pairs ($L = -1$) do not contribute to the update of the gradients in the optimization process as their distance is already larger than $\mu$ parameter in Eq. (1). To address this issue hard negative mining was proposed to include more negative pairs in the training. The hardest negative training pairs were identified by their distance and a subset of these examples were re-fed to the network for gradient update in each iteration.

3.2.2 SoftPN loss

We extend the idea of hard negative mining by incorporating both, positive and negative examples simultaneously in a new loss function. It uses a triplet of patches where two pairs represent a form of soft negative mining without the need for extra back propagation of specific hard negatives through the network [20].

Any training triplet $T = \{p_1, p_2, n\}$ includes two negative $\Delta(p_1, n)$, $\Delta(p_2, n)$ and one positive $\Delta(p_1, p_2)$ distance. Our proposed formulation of the loss function arises
from the triplet CNN architecture illustrated in Figure 1 (bottom). It is based on the intuitive idea that the smallest negative distance within the triplet should be larger than the positive distance. Ideally, we require the positive distance to reach 0 and the two negative distances to increase towards +∞. Therefore the smaller negative distance is the soft negative. Identification of such pair requires much less computation than mining of hard negatives and back propagating them through the network after every iteration. Formally our SoftPN objective is

$$l(T) = \left[ \left( \frac{e^{\Delta(p_1,p_2)}}{e^{\min(\Delta(p_1,n),\Delta(p_2,n))}} + e^{\Delta(p_1,p_2)} \right)^2 + \left( \frac{e^{\min(\Delta(p_1,n),\Delta(p_2,n))} + e^{\Delta(p_1,p_2)}}{e^{\min(\Delta(p_1,n),\Delta(p_2,n))}} - 1 \right)^2 \right]$$

(2)

Given $\Delta^* = \min(\Delta(p_1,n),\Delta(p_2,n))$ as the soft negative distance, the goal of the loss function is to force $\Delta^*$ to be larger than $\Delta(p_1,p_2)$. Note that unlike in the Hinge Embedding loss, negative distances always contribute to the optimization and in contrast to the previous works on triplet based learning \cite{12,22}, our negative loss includes both negative distances $\Delta(p_1,n),\Delta(p_2,n)$. The SoftMax Ratio objective introduced in \cite{12} is based on triplets and ratios, but does not include the evaluation of the $\Delta^*$ distance inside the triplet. An illustration of the the hinge loss objective \cite{25,20,22}, the SoftMax Ratio \cite{12} and the proposed SoftPN loss function is presented in Figure 3.

Figure 4 visualises two layers of the CNN for the proposed PN-Net as well as for DeepCompare \cite{25}. Convolutional filters of PN-Net seem to be more smooth e.g. more regularised compared to DeepCompare. We believe it is the effect of simultaneous use of positive and negative pairs in the loss function during training. In Figure 5 we compare the effect different loss functions discussed in this section have on the matching performance of learnt descriptors. We plot the 95% error in matching patches from patch dataset \cite{16}, and show how it decreases with each training epoch. A first observation is that the triplet based learning is significantly better for learning feature descriptors than the state of the art siamese pair based learning. This is demonstrated by the large difference between the siamese & hinge margin architecture compared to the proposed PN-Net architecture. The final error rate is 15% lower for SoftPN. Next, by comparing results for SoftMax and SoftPN to hinge loss we conclude that using triplets of data points as training examples leads to much better results than using pairs.

We also note that the proposed SoftPN loss function outperforms SoftMax Ratio function, due to the soft negative mining by $\Delta^*$ distance. Moreover, already the first epoch \textit{(i.e. after 2mins)} of training a local feature descriptor with the proposed method leads to the matching error rate of 9% when training the network with the Liberty dataset and testing in the Notredame dataset. This is much lower error than many recent descriptors achieve after extensive training as we show in section 4.

Another important note is that for training and comparing different loss functions we use the same set of patches. There are three times more pairs in this set than triplets therefore the siamese network with hinge loss uses three times more training examples than TripletNet with SoftMax and PN-Net with SoftPN. This is a significant advantage for the siamese network, yet the results indicate that the training is much more effective with triplets. It is also more efficient due to use of less training examples.
3.3. Implementation details

PN-Net and the siamese networks used the same underlying CNN in the experiments above. Also, unlike in [25] and [11] there is no extra layer that learns a distance metric between the two patches. Our simplified CNN architecture allows more efficient descriptor extraction and the use of $L_2$ norm for matching. Thus, a descriptor is obtained by processing a patch by a single branch of the network. The parameters of the network used in all our experiments are presented in Table 1.

Table 1: Architecture of the CNN used in the experiments. Patches of size $32 \times 32$ are used as input. The number in each convolutional layer denotes the number of the output planes that the convolution produces.

| Layer # | Description                      |
|---------|----------------------------------|
| 1       | Spatial Convolution(7,7) $\rightarrow$ 32 |
| 2       | Tanh                               |
| 2       | MaxPooling(2,2)                    |
| 3       | Spatial Convolution(6,6) $\rightarrow$ 64 |
| 4       | Tanh                               |
| 5       | Linear $\rightarrow$ \{128, 256\} |
| 6       | Tanh                               |

Our implementation is in Torch [6]. The training is done using $\approx 1.2M$ triplets generated on-the-fly using the patches from [16]. In contrast to how CNNs are typically trained including DeepCompare and MatchNet we do not use data augmentation. This is to make the training more efficient and to demonstrate that the improvements result from the approach and not from larger number of patches used for training.

In forming the triplets we choose randomly a pair of patches from the same 3D point, and subsequently we complete the triplet with a randomly chosen patch from another 3D point. This is in contrast to other works where carefully designed schemes of choosing the training data are used in order to enhance the performance [22, 11].

For the optimization the Stochastic Gradient Descend [3] is used, and the training is done in batches of 128 items, with a learning rate of 0.1, momentum of 0.9 and weight decay of $10^{-6}$.

The convolution methods are from the NVIDIA cuDNN library [5]. The training of a single epoch with $\approx 1.2M$ training triplets takes approximately 2 minutes in an NVIDIA Titan X GPU.

It is worth noting that the CNN used in our experiments consists of only two layers, while all of the other state-of-the-art deep feature descriptors consist of 3 layers and above [25] [20] [11]. Several other implementation variants could be added such as using different non-linearity layers (e.g. ReLU as in [11, 25]), extra normalization layers, but the main focus of our work is to show the effect of learning local features with triplets coupled with the SoftPN loss function. Sample results for other network configurations are presented in the supplementary material.

4. Experimental evaluations

In this section we evaluate the proposed local feature descriptor within the two most popular benchmarks in the field of local descriptor matching. We compare our method to SIFT [15], Convex optimization [21] the recently introduced MatchNet [11] and DeepCompare [25] descriptors which are currently the state of the art in terms of matching accuracy. The original code available from the authors was used in all the experiments. Code for other recent methods e.g. DSP-SIFT was not available at the time of this experiment.

Note that for a fair comparison, we use the siamese architectures similar to the one in DeepCompare, but we do not use the multi-scale 2ch architectures. Multi-scale approaches uses multiple patches from each example, with one being a cropped sub-patch around the center. This introduces information from different samples in the size-space and it has been shown to lead to significant improvements in terms of matching accuracy [17]. Such approach can be uses for various descriptors (e.g. MatchNet-2ch, PN-Net-2ch etc.).

It would be interesting to evaluate the effect of mining in terms of a siamese network learning as it was proposed in [20], however the implementation is not available yet.

4.1. Photo Tour dataset

We first evaluate the performance in terms of matching accuracy in distinguishing positive from negative patch pairs on the Photo Tour dataset [16]. This dataset consists of three subsets {Liberty, Yosemite, NotreDame} containing more than 500k patch pairs extracted around specific feature points. We follow the protocol proposed in [16] where the ROC curve is generated by thresholding the distance scores between patch pairs. The number reported here is the false positive rate at 95% true positive rate. For the evaluation we use the 100K patch pairs proposed by the authors.

The results for each of the combinations of training and testing using the three subsets of the Photo Tour dataset are shown in Table 2. The average across all possible combinations is also shown. Our PN-Net outperforms the state of the art for a single scale siamese CNN architecture (MatchNet). Moreover, our network does not learn an explicit distance metric and the final layer gives 128 dimensional descriptor in contrast to 4096 of MatchNet. Note that the performance gain is even greater when comparing to DeepCompare descriptors from [25], event though their dimen-
Table 2: Results form the Photo-Tour dataset [16]. Numbers are reported in terms of error at 95% correct. Bold numbers indicate the best performing descriptor. Note the significant reduction in dimensionality by PN-Net, together with the improvements over the state-of-the art results.

| Training  | Notredame | Liberty | | Notredame | Liberty | | Yosemite | Liberty | |
|-----------|-----------|---------| | | | | | |
| Descriptor | # features | mean | | mean | | | mean | |
| SIFT [15]  | 128       | 27.29   | 29.84 | 22.53 | 26.55 |
| ConvexOpt[21] | ≈ 80 | 10.08 | 11.63 | 11.42 | 14.58 | 7.22 | 6.17 | 10.28 |
| DeepCompare siam [25] | 256 | 13.21 | 14.89 | 8.77 | 13.48 | 8.38 | 6.01 | 10.07 |
| pseudo-siam [25] | 256 | 12.64 | 12.5 | 12.87 | 10.35 | 5.44 | 3.93 | 9.62 |
| MatchNet [11] | 512 | 11 | 13.58 | 8.84 | 13.02 | 7.7 | 4.75 | 9.82 |
| no bottleneck [11] | 4096 | 8.39 | 10.88 | 6.90 | 10.77 | 5.76 | 3.87 | 7.75 |
| PN-Net | 128 | 7.74 | 7.45 | 8.27 | 9.76 | 4.45 | 3.81 | 7.26 |
| PN-Net | 256 | 7.21 | 8.99 | 8.13 | 9.65 | 4.23 | 3.71 | 6.98 |

sionality is still twice larger than from PN-Net. Moreover, our descriptor outperforms all the others, except in the combination of training in Notredame and testing in Liberty. We can also observe that there is not much difference in performance when comparing the 128 with the 256 variants of PN-Net. It is important to mention that the proposed descriptor achieves state of the art performance without any data augmentation during training, in contrast to the competing CNN based methods [25, 11]. Smaller network and no data augmentation or multi-scale examples leads to much faster learning, yet our PN-Net and SoftPN loss achieves similar or better performance after 1 epoch (2min) than DeepCompare [25] after 2 days of training. Full plots of the ROC curves can be found in the supplementary material.

4.2. Oxford image sequences

We also test the performance of the proposed descriptor in terms of matching local features between two images based on the benchmark from [17].

Evaluation protocol. As discussed in the introduction the original protocol has been loosely followed in various papers leading to not comparable results. To address this issue, we draw ideas from the successful Photo Tour benchmark. To increase the size of the dataset we complement the eight sequences with additional seven that include illumination, rotation and scale changes. The images are acquired in a similar way to the original eight with pair-wise image homographies for establishing correspondence ground truth. Note that unlike [9], the sequences are not generated artificially by warping single images to various transformations, but they come from naturally captured images together with the noise introduced by varying imaging conditions. Next, we apply an interest point detector to identify regions with varying image content. In contrast to the Photo Tour [16] that extracted keypoints with scale-invariant DoG, we use affine invariant Harris-Affine. This makes the patches complementary to the Photo Tour and introduces a different type of noise resulting from the affine detector inaccuracy. We establish correspondence ground truth using the homographies and the overlap error from [17]. We consider two points in correspondence if the overlap error between the detected regions is less than 50%. Note that a region from one image can be in correspondence with several regions from the other image. By reducing each image pair to a collection of patches, the benchmark will eliminate some of the varying factors such as the choice of the interest point detector, the number of extracted patches, their sizes, etc. The data includes 15 sequences, each consisting of 6 images with increasing degree of change in viewing conditions. Each image has an associated set of 1k patches. A pair of images has an associated text file indicating the overlap error between the patches that overlap by at least 50%. This data will be available online and together with Photo Tour will allow to test additional properties of new descriptors such as robustness to different type of noise and generalisation from one dataset to the other. Note that the results for Oxford data presented here are not directly comparable to those reported in other papers. However this has been the case for many papers and we believe that using patches will allow converging to repeatable experiments on this data. The descriptors performance is evaluated in terms of nearest neighbour matching and the results are presented with precision-recall curves as it was originally proposed in [17]. More specifically, for each patch from the left image we find its nearest neighbour in the right image. Based on the ground truth overlap we can distinguish between false positives and true positives, and generate precision-recall curves. Detailed description of the dataset and the benchmarking protocol can be found in the supplementary mate-
In this experiment all the CNN networks are trained using Libery data from Photo Tour. In Figure 6 we present the precision-recall curves across all the pairs of graffiti and trees images, which are considered the most challenging sequence in the dataset. MatchNet and the proposed PN-Net are close in terms of the area under the curve, although PN-Net outperforms MatchNet and DeepCompare in both sequences in particular in trees. Clearly DeepCompare struggles with image blur which confirms the observations in [25]. We include precision recall curves for the other sequences in the suplementary material.

Some examples of true and false positive matches between several image pairs are shown in Figure 7. True positives are shown in the top row, and false positives in the bottom. The patches show extreme affine deformation, scale changes, rotation error due to inaccuracy of the Harris-Affine detector as well as the interpolation noise resulting from normalisation from ellipses to circles. Some of the correct matches by PN-Net are impressive given that the network was not trained on such errors as they don’t occur in Photo Tour data. Also some of the false positives exhibit some visual similarity to be considered as reasonably expli- ciable.

To compress the results we use the mean average precision (mAP) which is defined as the area under the precision recall curve. The mAP for different methods and image sequences is presented in Fig. 8. First observation is that the scores for the new images fall between the graffiti and the ube sequence, which are typically the most and the least challenging ones in the original data. More importantly, the PN-Net_256 outperforms the matching results of MatchNet by 2% in terms of mAP averaged across all the sequences, even though MatchNet descriptor consists of 4095 dimen-

Figure 6: Precision-Recall curves for matching performance tested on Oxford data. Results for the two challenging sequences: graffiti (left) with affine deformations and trees (right) with blur and out of focus images. Our PN-Net gives top scores for both sequences.

Figure 7: Examples of true (top) and false positive (bottom) nearest neighbour matching in a large patch dataset. Note the extreme variations that the proposed descriptor can cope with.
practical problems with large datasets.

Note that several works have attempted to port SIFT to GPU [2], with speedups ranging from 5 to 20 compared to the CPU version. Even when considering such speedups, the proposed descriptor is still faster to compute mainly due to the convolutional operations libraries [5].

Note that the proposed PN-Net descriptor also has an advantage in the computational efficiency during training time. While other works mention that their optimizations take from several hours [21] to 2 days [25] [11], our work reaches state of the art performance in 100-200 training epochs, which translates to 2-5 hours training on a single GPU. Surprisingly even after a single epoch, i.e. after two minutes of training, we get a descriptor very close to the state of the art.

5. Conclusion

This work introduced a new approach to training CNN architecture for extracting local image descriptors in the context of nearest neighbour matching. It is based on the recent advancements in the area of convolutional neural networks and deep learning. It makes use of the ideas introduced in the field of distance metric learning and online boosting by training with positive and negative constraints simultaneously.

We have introduced a novel loss function SoftPN that is based on triplets of patches extracted from feature points. It incorporates the idea of hard negative mining within the loss function thus avoid mining and retraining of the network after each iteration. The experimental results show that SoftPN leads to faster convergence and lower error than hinge loss or SoftMax ratio.

Moreover, the results show that using triplets for training results in a better descriptor and faster learning. The networks can be made simpler, trained with less examples and extract descriptors with a speed comparable to BRIEF. Also the dimensionality can be significantly reduced compared to other CNN based descriptors. We believe that due to these properties the proposed network is less prone to over-fitting. This is supported by the results showing good generalisation properties.

In addition, we proposed a new protocol for evaluating feature matching that aims to correct the significant discrepancies between the protocols used in various experiments and ambiguities in interpreting the results of descriptor performance evaluations in future papers. We added more image sequences to the frequently used Oxford dataset [17]. The dataset, the ground truth and the source code of the proposed PN-Net descriptor are available from [https://github.com/vbalnt/pnnet].

We believe that the proposed PN-Net descriptor with its very efficient computation, low memory requirements and state of the art performance will enable new real-time applications that are based on a new family of highly accurate but extremely fast deep feature descriptors. We also believe that this work sets a positive example that there is no need to compromise the efficiency of the descriptor to achieve state of the art performance with CNN architectures.

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