Interpretable and Generalizable Deep Image Matching with Adaptive Convolutions

Shengcai Liao and Ling Shao
Inception Institute of Artificial Intelligence (IIAI), Abu Dhabi, UAE
{scliao,ling.shao}@ieee.org

Abstract

For image matching tasks, like face recognition and person re-identification, existing deep networks often focus on representation learning. However, without domain adaptation or transfer learning, the learned model is fixed as is, which is not adaptable to handle various unseen scenarios. In this paper, beyond representation learning, we consider how to formulate image matching directly in deep feature maps. We treat image matching as finding local correspondences in feature maps, and construct adaptive convolution kernels on the fly to achieve local matching. In this way, the matching process and result is interpretable, and this explicit matching is more generalizable than representation features to unseen scenarios, such as unknown misalignments, pose or viewpoint changes. To facilitate end-to-end training of such an image matching architecture, we further build a class memory module to cache feature maps of the most recent samples of each class, so as to compute image matching losses for metric learning. The proposed method is preliminarily validated on the person re-identification task. Through direct cross-dataset evaluation without further transfer learning, it achieves better results than many transfer learning methods. Besides, a model-free temporal cooccurrence based score weighting method is proposed, which improves the performance to a further extent, resulting in state-of-the-art results in cross-dataset evaluation.

1 Introduction

Image matching is an important and fundamental task in computer vision, which has various applications ranging from image registration, 3D scene reconstruction, image retrieval, and so on. Traditionally, it has an active research in feature detection (e.g. SIFT [38], SURF [4]) and feature matching. This is particularly useful for matching unaligned images.

In terms of matching aligned or roughly aligned images, such as face images or person images, it is generally regarded that a canonical feature representation from the image is more important than doing local feature matching in traditional way of computer vision. This is supported from traditional holistic features like PCA [53] and LDA [69], statistical representation of local features like LBP [1] and Gabor [34], to modern deep representations [52, 50, 40]. However, a precondition is that the images being represented should be well aligned, especially for traditional methods. Therefore, keypoint or landmark detection is usually applied in advance of the feature representation, but misalignment still occasionally happens. Regarding person re-identification, automatic person detection still lacks satisfactory solutions. Researchers also apply keypoint detection to facilitate person re-identification, though person keypoint detection in surveillance video frames is itself a challenge. On the other hand, attention based deep representation learning [39, 63, 35, 42, 61, 28, 37, 64] goes beyond explicit alignment for feature extraction. It is able to find saliency features in images for feature representation, so as to alleviate the requirement of precise alignment.

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However, most existing methods compute a fixed representation vector, also known as feature vector, for each image, and perform ad-hoc distance or similarity metric (e.g. Euclidean distance or Cosine similarity) for image matching. Without domain adaptation or transfer learning, the learned model is fixed as is, which is not adaptable to handle various unseen scenarios. Even with an attention model, the learned attention mechanism might be limited in the source domain scenario, but not very responsive to unseen image content. Therefore, when generalization ability is a concern, it is expected to have an adaptive ability for the given model architecture.

In this paper, beyond representation learning, we consider how to formulate adaptive image matching directly in deep feature maps. While how deep neural network works is still a mystery, we suppose it does have strong representation capability in deep layers, though a black box, and we try to interpret its behaviour in the final image matching step. Specifically, we treat image matching as finding local correspondences in feature maps, and construct adaptive convolution kernels on the fly to achieve local matching (see Fig. 1). In this way, the learned model enjoys adaptive convolution kernels in the final layer, specific to each image, and the matching process and result is interpretable (see Fig. 2), similarly viewed as in traditional feature correspondence approaches [38,3]. Probably because finding similar local features through adaptive convolution is a common characteristic among different domains, this explicit matching is more generalizable than representation features to unseen scenarios, such as unknown misalignments, pose or viewpoint changes. We call this adaptive convolution AdaConv. To facilitate end-to-end training of such an image matching architecture, we further build a class memory module to cache feature maps of the most recent samples of each class (see Fig. 3), so as to compute image matching losses for metric learning.

The proposed method is preliminarily validated on the person re-identification task, where domain adaptation is an active research area. Through direct cross-dataset evaluation without further transfer learning, the proposed method achieves better results than many transfer learning methods. Besides, to explore the prior spatial-temporal structure of a camera network, a model-free temporal cooccurrence based score weighting method is proposed, which we call Temporal Lifting (TLift). The basic idea is that nearby persons in one camera are potentially still nearby in another camera (see Fig. 4). Therefore, their corresponding matches in other cameras can be served as pivots to enhance the weight of their own nearby persons. This is also computed on the fly for each query image, without
statistical learning of a transition time model in advance. As a result, TLift improves the person re-identification performance to a further extent, resulting in state-of-the-art results in cross-dataset evaluation.

To summary, the novelty of this work is two-folds: (i) a new deep image matching approach with adaptive convolutions, along with a class memory module for end-to-end training, and (ii) a model-free temporal cooccurrence based score weighting method. The advantages of this work are also two-folds. First, the proposed image matching method is interpretable, it is well suited in handling misalignments, pose or viewpoint changes, and it also generalizes well in unseen domains. Second, both AdaConv and TLift can be computed on the fly, and they are complementary to many other methods. For example, AdaConv does not require transfer learning, but can be served as a better pre-learned model for transfer learning methods, and TLift can be readily applied by most person re-identification algorithms as a post-processing step.

2 Related Works

Many existing person re-identification approaches try to build a robust feature representation which is both distinctive and stable for describing a person’s appearance under various conditions [20,14,17,58]. Besides the research of robust features, metric learning approaches have been widely used in person re-identification [59,11,8,71,24,30,16,15]. As for modern deep learning approaches, there are a lot of recent approaches that improve the person re-identification performance a lot [65,51,55,46,7,8]. However, due to limited labeled training data and a big diversity in real-world surveillance, deep person re-identification methods usually has poor generalization ability in unseen scenarios. To address this, a good number of unsupervised transfer learning or domain adaption approaches are proposed for person re-identification [77,76,10,2,29,57,13,48]. Yet these approaches require further training on the target domain, though mostly unsupervised or self-supervised. In practical applications, the end-device may have limited computation power to support deep CNN training. Therefore, improve the baseline model’s generalization ability is still an urgent need.

3 Adaptive Convolution

3.1 Image Matching via Adaptive Convolution

Convolution can be used as a kind of template matching process. It has a convolution kernel, either pre-defined (e.g. differential template for edge detection [4]) or learned (e.g. convolutional neural network, CNN [25]). The convolution kernel is usually a local template, and the convolution process is to slide the template over the whole input image, with the output result being the matching response to the given template, where larger response values indicate better local matches. Therefore, in a modern deep CNN, the kernel parameters to be learned play an important role for what kind of pattern the network is seeking for.

However, once being trained in a training dataset, the convolution kernels in a CNN network are fixed as is, and so they can only what they have already remembered from the training data. In case the application domain is different from the source domain of the training, it is likely that the learned model is less responsive to unseen image content due to fixed convolution kernels.

For the image classification task, it only involve one single image, and classification can be viewed as the matching between the input image and the learned model. The model can only give a decision to known classes. However, the image matching task always involve a pair of images, and it is usually an open-class problem. That is, the input images are usually with unknown new classes, for example, in case of face recognition or person re-identification. Most existing methods do not directly consider the relationship between the two input images under matching, but instead, like classification, they treat each image independently and apply the learned model to extract a fixed feature representation. Then, image matching is simply a distance measure between two representation vectors, regardless of the direct relationship between the actual contents of the two images.

Therefore, in this paper, we consider the relationship between two images, and try to formulate adaptive image matching directly in deep feature maps. Specifically, we treat image matching as finding local correspondences in feature maps, and construct adaptive convolution kernels on the fly to achieve local matching. As illustrated in Fig. 1, each input image is first feed forwarded into a
backbone CNN, resulting in a final feature map of size $[1, d, h, w]$, where $d$ is the number of output channels, and $h$ and $w$ are height and width of the feature map, respectively. Then, the channel dimension of both feature maps under matching is normalized by the $\ell_2$-norm. After that, one of the feature maps is permuted and reshaped into $[h \times w, d, 1, 1]$ as a normalized convolution kernel, with input channels $d$, output channels $h \times w$, and kernel size $1 \times 1$. This acts as an adaptive convolution kernel, with parameters constructed on the fly from the input, in contrast to the fixed convolution kernels in the learned model. Upon this, the adaptive kernel can be used to perform convolution on the normalized feature map of another image. The result is $[1, h \times w, h, w]$. Since feature channels are $\ell_2$-normalized, the convolution in fact measures the Cosine similarity on every location of the two feature maps. Besides, since the convolution kernel is adaptively constructed from the image content, these similarity values exactly reflects local match results between the two input images. Therefore, an additional global max pooling (GMP) operation will output the best local matches, and the maximum indices found by GMP indicate the best locations of local correspondences that can be further used to interpret the matching result, as illustrated in Figs. 1 and 2.

Note that by matching only two images, the above process can also be done by matrix multiplication. However, when a batch of images is considered, convolution is more suited and more efficient. Note also that the global max pooling can also be done by reshaping the $[1, h \times w, h, w]$ similarities and maximizing along the $h \times w$ channels. That is, seeking the best matches can be taken in both sides of the images. Concatenating the output will result in a $2 \times h \times w$ similarity vector for each pair of images.

### 3.2 Network Architecture

The architecture of the proposed adaptive convolution based image matching method is shown in Fig. 3, which consists of a backbone CNN, the AdaConv layer for local matching, a class memory layer for training, which will be introduced in the subsequent subsection, a global max pooling layer, a BN-FC-BN block, and finally a similarity output by a sigmoid function for evaluation in test phase or loss computation in training phase. The input sizes of the BN-FC-BN block are all $2 \times h \times w$. The output size of the FC layer is 1, which acts as a binary classifier or a similarity metric, indicating whether one pair of images belong to the same class or not. The two BN (batch normalization) layers are all one-dimensional, which are used to normalize the similarity output and stable the gradient in training.

### 3.3 Class Memory and Update

To train the AdaConv image matching architecture, we need to form sufficient training image pairs. A nature way is to use mini batches for training, and form image pairs within each mini batch. However, this is not efficient to sample the whole training set and the convergence is slow, considering the $N^2$ combinations of all samples where $N$ is the number of training images. Therefore, we propose a class memory module to facilitate the end-to-end training of the AdaConv network. Specifically, a $[c, d, h, w]$ tensor buffer is registered, where $c$ is the number of classes. For each mini batch of size $b$,
3.4 Loss Function

With mini batch of size \([b, d, h, w]\) and class memory of size \([c, d, h, w]\), a \(b \times c\) pairs of similarity values will be computed by AdaConv. We use a sigmoid function to map the similarity values into \([0, 1]\), and compute the binary cross entropy loss. Considering that the number of negative pairs are far more than that of the positives, to enable online hard negative mining while reducing the influence of mass of negative pairs, we also apply the focal loss \([32]\) to weight the binary cross entropy. That is,

\[
\ell(\theta) = -\frac{1}{bc} \sum_{i=1}^{b} \sum_{j=1}^{c} (1 - \hat{p}_{ij}(\theta))^{\gamma} \log(\hat{p}_{ij}(\theta)),
\]

where \(\theta\) is the network parameter, \(\gamma\) is the focusing parameter, by default \(\gamma = 2\) as suggested in \([32]\), and

\[
\hat{p}_{ij} = \begin{cases} 
  p_{ij} & \text{if } y_{ij} = 1, \\
  1 - p_{ij} & \text{otherwise}, 
\end{cases}
\]

where \(y_{ij} = 1\) indicates positive pair while negative pair otherwise, and \(p_{ij} \in [0, 1]\) is the probability output of the sigmoid function.

4 Temporal Lifting

For the task of person re-identification, to explore the prior spatial-temporal structure of a camera network, a model-free temporal cooccurrence based score weighting method is proposed, which we call Temporal Lifting (TLift). Fig. 4 illustrates the idea. A basic assumption is that nearby persons in one camera are potentially still nearby in another camera. Therefore, their corresponding matches in other cameras can be served as pivots to enhance the weight of their own nearby persons. In Fig. 4, \(A\) is the query person. \(E\) is more similar than \(A'\) to \(A\) in another camera. With nearby persons \(B\) and \(C\), and their top retrievals \(B'\) and \(C'\) acting as pivots, the matching score of \(A'\) can be temporally lifted since it is a nearby person of \(B'\) and \(C'\), while the score of \(E\) will be reduced since there is no such pivot.
since it is a nearby person of $B'$ and $C'$, while the matching score of $E$ will be reduced since there is no such pivot. Formally, suppose $A$ is the query person in camera $Q$, the set of nearby persons to $A$ in camera $Q$ is defined as

$$R = \{B | \Delta T_{AB} < \tau, \forall B \in Q\},$$  

where $\Delta T_{AB}$ is the time difference between persons $A$ and $B$, and $\tau$ is a threshold on $\Delta T$ to define nearby persons. Then, for each person in $R$, person retrieval will be performed on other cameras with the AdaConv similarity measures, and the top K retrievals are defined as the pivot set $P$. Then, each person in the pivot set $P$ is acted as an ensemble point for one-dimensional kernel density estimation on time differences, and the matching probability between $A$ and any person $X$ in other cameras will be computed as

$$p_{AX} = \frac{1}{|P|} \sum_{B \in P} e^{-\frac{\Delta T_{BX}^2}{2\sigma^2}},$$

where $\sigma$ is the sensitivity parameter of the time difference. Then this temporal probability is used to weight the similarity score of the AdaConv by a multiplication fusion. In this way, true positives nearby pivots will be lifted, while hard negatives far from pivots will be suppressed. Note that this is also computed on the fly for each query image, without statistical learning of a transition time model in advance. Therefore, it does not require training data, and can be readily applied by many other person re-identification methods.

5 Experiments

5.1 Implementation Details

The proposed method is implemented in PyTorch. The AdaConv has no hyper parameters. Parameters for TLift are $K = \tau = \sigma = 100$. We used an adapted version of the open source person re-identification library (open-reid) package by [78] with random erasing enabled. Person images are resized to $384 \times 128$. The backbone network is the Resnet152 [18], pre-trained on ImageNet. We used the layer3 feature map for all the experiments, since the size of the layer4 feature map is too small. The batch size of samples for training is 32. The SGD optimizer is applied, with a learning rate of 0.001 for the backbone network, and 0.01 for newly added layers. It is decayed by 0.1 once until convergence, monitored by the ReduceLROnPlateau module in PyTorch.

5.2 Datasets

Experiments were evaluated on two large person re-identification datasets, Market-1501 [70] and DukeMTMC-reID [12, 73], with frame numbers available so that we are able to evaluate the proposed TLift method. The Market-1501 dataset contains 32,668 images of 1501 identities captured from 6 cameras. There are 12,936 images from 751 identities for training, and 19,732 images from 750 identities for testing. The DukeMTMC-reID is a subset of the multi-target and multi-camera pedestrian tracking dataset DukeMTMC [12]. It includes 1,812 identities and 36,411 images in which 16,522 images of 702 identities are used for training, 2,228 images of another 702 identities are used as query images, while the remaining 17,661 images are used as gallery images. Cross-dataset evaluation was performed in these two datasets, by training on the training subset of one dataset, and evaluating the performance on the test subset of another dataset.

The DukeMTMC-reID dataset has a good global and continuous record of frame numbers, and it is synchronized by providing offset times. While on the Market-1501 dataset, it only has independent frame numbers in each session of videos in each camera. For several sessions in each camera, we roughly calculated the overall time frames of each session as offset, and made a cumulative record by assuming the video sessions were continuously recorded.

The cumulative matching characteristic (CMC) and mean Average Precision (mAP) are used as the performance evaluation metrics. All evaluations are under the single-query evaluate protocol.

5.3 Ablation Study

We first evaluate the influence of the backbone networks and the input image size. The results are shown in Table 1, where H256 means the input image size of $256 \times 128$, while H384 means $384 \times 128$. 
Table 1: Comparison of different backbone networks.

| Backbones | Duke→Market | Market→Duke |
|-----------|-------------|-------------|
|           | Rank-1 mAP  | Rank-1 mAP  |
| Resnet50  | H256 60.4   | 40.7 24.5   |
|           | H384 60.0   | 41.9 25.8   |
| Resnet152 | H256 60.7   | 47.1 27.8   |
|           | H384 61.9   | 49.4 29.3   |

Table 2: Comparison of different metric/loss layers. RR means re-ranking enabled.

| Metric / Loss | RR | Duke→Market | Market→Duke |
|---------------|----|-------------|-------------|
|               |    | Rank-1 mAP  | Rank-1 mAP  |
| Softmax-CE    |   | 42.0        | 24.6        |
| Center loss   |   | 42.3        | 33.7        |
| AdaConv       |   | 61.9        | 49.4        |
|               | ✓ | 48.3        | 30.2        |
|               | ✓ | 46.9        | 39.0        |
|               | ✓ | 66.5        | 55.5        |

From the results it can be observed that H384 performs slightly better than H256, especially for Market→Duke, and with the Resnet152 backbone. Regarding the backbones, for Duke→Market, the performances of all results are comparable. However, for the Market→Duke experiments, there is a good improvement of Resnet152 over Resnet50. Therefore, we used Resnet152 in the following experiments, with 384 × 128 input image size.

With the same backbone network Resnet152 and input image size 384 × 128, we also implemented two baseline methods for comparison. One is with the classical softmax based cross entropy (CE) loss, and the other one is the center loss [60]. The comparison results to the proposed AdaConv are shown in Table 2. From the comparison results it is obvious that the proposed AdaConv method improves the baseline by a large margin. One may argue that there are still other choices better than the softmax cross entropy and center losses, like Sphereface [36] and ArcFace [9]. However, from their study the improvement over the softmax cross entropy baseline is not a significant boost, and in our experience in person re-identification different configurations of losses do not cause large differences. Therefore, we may conclude that the large improvement observed here is due to the new image matching way we designed, instead of different loss configurations.

Further more, to understand the role of re-ranking, we also applied the k-reciprocal encoding based re-ranking method [67]. The results are also listed in Table 2. It can be seen that all methods observed a large improvement by enabling the re-ranking. Besides, it appears that the AdaConv method gains more larger improvements than other baselines. This is probably because the image matching mechanism of AdaConv better measures the similarity between images, and so the reverse neighbor based re-ranking method benefits from better similarity measures.

Next, we evaluate the contribution of TLift, shown in Table 3. Again we can observe a large improvement by employing TLift to explore temporal information, and this improvement is complementary to re-ranking so that they can be combined.

Table 3: Role of re-ranking (RR) and TLift.

| Method       | Duke→Market | Market→Duke |
|--------------|-------------|-------------|
|              | Rank-1 mAP  | Rank-1 mAP  |
| AdaConv      | 61.9        | 49.4        |
| AdaConv+RR   | 66.5        | 55.5        |
| AdaConv+RR+TLift | 78.8     | 77.8        |
Table 4: Comparison of state-of-the-art cross-dataset results (%) from DukeMTMC-reID to Market-1501. TL means transfer learning using the Market-1501 training set.

| Method            | Pub       | TL | Rank-1 (%) | mAP (%) |
|-------------------|-----------|----|------------|---------|
| PUL [13]          | TOMM18    | ✓  | 44.7       | 20.1    |
| CAMEL [66]        | ICCV17    | ✓  | 54.5       | 26.3    |
| TJ-AIDL [57]      | CVPR17    | ✓  | 58.2       | 26.5    |
| SPGAN [10]        | CVPR18    | ✓  | 58.1       | 26.9    |
| HHL [76]          | ECCV18    | ✓  | 62.2       | 31.4    |
| BUC [33]          | AAAI18    | ✓  | 66.2       | 38.3    |
| TAUDL [26]        | ECCV18    | ✓  | 63.7       | 41.2    |
| UTAL [27]         | PAMI19    | ✓  | 69.2       | 46.2    |
| UDARTP [48]       | arXiv18   | ✓  | 75.8       | 53.7    |
| AdaConv           |           |    | 61.9       | 30.8    |
| AdaConv+RR        |           |    | 66.5       | 47.9    |
| AdaConv+RR+TLift  |           |    | **78.8**   | **54.4**|

5.4 Comparison to the State of the Arts

There are a great number of person re-identification methods since this is a very active research area. Here we only list recent results for comparison. For the cross-dataset evaluation Duke→Market, the results are listed in Table 4. It can be observed that our AdaConv method without transfer learning performs better than four transfer learning methods, indicating that it enables the network to learn how to match two images, and the learned model generalizes well in unseen domain. Besides, by enabling re-ranking and TLift, we achieve the state-of-the-art result in this scenario. The re-ranking and TLift methods can also be applied by other methods, though. Therefore, we list their results separately. However, both of them are calculated on the fly without learning in advance, so together with AdaConv, it appears that a good model can also be applied with good generalization ability without further domain adaptation.

For the cross-dataset evaluation Market→Duke, the results are listed in Table 5. It can be observed that our AdaConv method without transfer learning performs better than 6 out of 12 recent transfer learning methods in rank-1, and 8 out of 12 in mAP. This could be understood as large improvement in cross-dataset evaluation, which is a better evaluation strategy for understanding generalization ability of algorithms. Besides, the final performance of AdaConv with re-ranking and TLift also achieves the new state of the art on Market→Duke, with 9.4% improvement in rank-1 and 9.9% improvement in mAP.

Finally, for a reference, we also list the within-dataset results on Market-1501 in Table 6 and on DukeMTMC-reID in Table 7. It can be observed that the AdaConv method is not the best one in within-dataset evaluation, indicating that good within-dataset evaluation performance may not be the necessary to understand an algorithm’s generalization ability. We achieve the best result among compared methods by AdaConv+RR+TLift, though.

5.5 Qualitative Analysis and Discussion

The unique characteristic of the proposed AdaConv method is its interpretable matching results. Therefore, we show some qualitative matching results in Table 5 for a better understanding of the proposed method. The model shown here is learned on the Market-1501 training data, and the evaluations are done on the query subsets of the Market-1501 and DukeMTMC-reID datasets. Results of both positive pairs and hard negative pairs are shown. It can be observed that the proposed method is able to find correct local correspondences of positive pairs of images, even if there are notable misalignments or pose/viewpoint changes. Besides, for hard negative pairs, the matching of AdaConv still appears to be mostly reasonable, by linking visually similar parts or even the same person (may be ambiguously labeled).

One drawback of AdaConv is that it requires more memory to run than other methods, and it needs to restore feature maps of images instead of features, where feature maps are generally larger in size than representation features. Besides, TLift can only be applied on datasets with good time records.
Figure 5: Examples of qualitative matching results by the proposed AdaConv method.
Table 5: Comparison of state-of-the-art cross-dataset results (%) from Market-1501 to DukeMTMC-reID. TL means transfer learning using the DukeMTMC-reID training set.

| Method     | Pub  | TL | Rank-1 | mAP  |
|------------|------|----|--------|------|
| UMDL [41]  | CVPR16 | ✓  | 18.5   | 7.3  |
| Ver+ID [74] | TOMM17 | ✓  | 25.7   | 12.8 |
| PN-GAN [43] | ECCV18 | ✓  | 29.9   | 15.8 |
| PUL [33]   | TOMM18 | ✓  | 30.4   | 16.8 |
| TJ-AIDL [57] | CVPR17 | ✓  | 44.3   | 23.0 |
| MMFA [31]  | BMVC18 | ✓  | 45.3   | 24.7 |
| SPGAN [10] | CVPR18 | ✓  | 46.9   | 26.4 |
| HHL [76]   | ECCV18 | ✓  | 46.9   | 27.2 |
| CFSM [6]   | AAAI19 | ✓  | 49.8   | 27.3 |
| BUC [33]   | AAAI18 | ✓  | 47.4   | 27.5 |
| ARN [29]   | CVPRW18 | ✓  | 60.2   | 33.4 |
| TAUDL [26] | ECCV18 | ✓  | 61.7   | 43.5 |
| UTAL [27]  | PAMI19 | ✓  | 62.3   | 44.6 |
| UDARTP [48] | arXiv18 | ✓  | 68.4   | 49.0 |
| AdaConv    |      |    | 49.4   | 29.3 |
| AdaConv+RR |      |    | 55.5   | 45.3 |
| AdaConv+RR+TLift | | | **77.8** | **58.9** |

Table 6: Comparison of state-of-the-art within-dataset evaluation results (%) on the Market-1501 database.

| Method      | Pub      | Rank-1 | mAP   |
|-------------|----------|--------|-------|
| DSR [19]    | CVPR18   | 83.6   | 64.2  |
| DML [68]    | CVPR18   | 87.7   | 68.8  |
| CamStyle+RR [77] | CVPR18 | 89.5   | 71.55 |
| AWTL [44]   | CVPR18   | 89.5   | 75.7  |
| HA-CNN [28] | CVPR18   | 91.2   | 75.7  |
| SPreID [23] | CVPR18   | 92.5   | 81.3  |
| PCB [51]    | ECCV18   | 93.8   | 81.6  |
| Mancs [54]  | ECCV18   | 93.1   | 82.3  |
| PSE+RR(ECN) [45] | CVPR18 | 90.3   | 84.0  |
| MGN [56]    | ACMMM18  | 95.7   | 86.9  |
| AdaConv     |          | 93.6   | 81.7  |
| AdaConv+RR  |          | 94.8   | 92.8  |
| AdaConv+RR+TLift |        | **97.6** | **94.0** |

Though this information is easy to obtain in real surveillance, most existing person re-identification datasets do not contain this information.

6 Conclusion

In this paper, beyond representation learning, we formulate image matching directly in deep feature maps and develop a deep image matching method called AdaConv. It is able to find local correspondences in feature maps by constructing adaptive convolution kernels on the fly for local matching. A good property of AdaConv is that its matching result is interpretable, and this explicit matching is more generalizable than representation features to unseen scenarios. A model-free temporal cooccurrence based score weighting method called TLift is also proposed, achieving a large improvement with time frames. The proposed method is preliminarily validated on the person re-identification task, resulting in state-of-the-art results in cross-dataset evaluation. In future researches, it is interesting to applying AdaConv to other image matching scenario such as face recognition.
Table 7: Comparison of state-of-the-art within-dataset evaluation results (%) on the DukeMTMC-reID database.

| Method       | Pub    | Rank-1 | mAP  |
|--------------|--------|--------|------|
| CamStyle [77] | CVPR18 | 78.3   | 57.6 |
| dMpRL [21]   | TIP18  | 76.8   | 58.6 |
| AACCN [62]   | CVPR18 | 76.8   | 59.3 |
| MLFN [5]     | CVPR18 | 81.2   | 62.8 |
| ATWL [44]    | CVPR18 | 79.8   | 63.4 |
| HA-CNN [28]  | CVPR18 | 80.5   | 63.8 |
| DuATM [47]   | CVPR18 | 81.8   | 64.6 |
| PAN+RR [75]  | TCSVT18 | 75.9  | 66.7 |
| PCB [51]     | ECCV18 | 83.3   | 69.2 |
| Part-aligned [49] | ECCV18 | 84.4 | 69.3 |
| SPreID [23]  | CVPR18 | 86.0   | 73.3 |
| DGNet [72]   | CVPR19 | 86.6   | 74.8 |
| MGN [56]     | ACMMM18 | 88.7  | 78.4 |
| PSE+RR [45]  | CVPR18 | 85.2   | 79.8 |
| AdaConv      |        | 83.8   | 71.4 |
| AdaConv+RR   |        | 87.7   | 86.3 |
| AdaConv+RR+T Lift |        | **95.0** | **91.1** |

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