HIERARCHICAL CROSS NETWORK FOR PERSON RE-IDENTIFICATION

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ABSTRACT
Person re-identification (person re-ID) aims at matching target person(s) grabbed from different and non-overlapping camera views. It plays an important role for public safety and has application in various tasks such as, human retrieval, human tracking, and activity analysis. In this paper, we propose a new network architecture called Hierarchical Cross Network (HCN) to perform person re-ID. In addition to the backbone model of a conventional CNN, HCN is equipped with two additional maps called hierarchical cross feature maps. The maps of an HCN are formed by merging layers with different resolutions and semantic levels. With the hierarchical cross feature maps, an HCN can effectively uncover additional semantic features which could not be discovered by a conventional CNN. Although the proposed HCN can discover features with higher semantics, its representation power is still limited. To derive more general representations, we augment the data during the training process by combining multiple datasets. Experiment results show that the proposed method outperformed several state-of-the-art methods.

Index Terms— Person re-identification, Deep learning, Convolutional Neural Networks

1. INTRODUCTION
Person re-ID aims at matching target person(s) grabbed from different and non-overlapping camera views. It plays an important role for public safety and has application in various tasks such as, human retrieval, human tracking, and activity analysis. Person re-ID is a very challenging task since it has to deal with many difficult problems, for example, low resolution of video camcorder, occlusion among objects, large intra-class scatter, etc. To tackle the above mentioned issues, learning robust and invariant features from a target image is important.

Recently, since the rise of deep learning, the performance on person re-ID has also dramatically been improved and many deep learning-based methods have been proposed. Although the structure of a conventional convolutional neural network (CNN) is able to powerfully learn general and semantic features from a target scene, there remain abundant un-use information distributed over layers of the networks.

To uncover the information embedded in layers of a CNN in a more efficient manner, several methods have been proposed [5, 6, 7]. In [5], Hariharan et al. proposed the hyper-column concept which asserts the concatenation of features from feature maps and makes it a long vector for matching. Long et al. [6] proposed the use of a DAG net to fuse the information coming from the fine layers and the coarse layers, respectively, and then obtain both local and global structures for further use. Lin et al. [7] proposed a feature pyramid network which exploits the inherent multi-scale information in network to enhance the object representation power. To better discover un-use information embedded in a CNN, we proposed a new network architecture called hierarchical cross network (HCN) to achieve the goal. In addition to the backbone model of a conventional CNN, HCN is equipped with...
two additional maps called hierarchical cross feature maps.

As shown in Figure[1], the maps of an HCN are formed by merging layers with different resolutions and semantic levels. With the hierarchical cross feature maps, an HCN can effectively uncover additional semantic features which could not be discovered by a conventional CNN.

Although the proposed HCN can discover features with higher semantics, its representation power is still limited. To derive more general representation, we augment the data during the training process by combining multiple datasets. Unlike many applications which deal with either classification or retrieval only, the task of person re-ID requires to handle both. Therefore, we divide the dataset into two non-overlapping subsets. We make the number of identities trained in the training stage a variable since this number will not be limited by the number of unseen identities during retrieval. Therefore, augmenting the dataset by combining many related datasets is feasible. With this combined dataset concept realized, the number of unseen identities during retrieval. Therefore, we divide the dataset into two non-overlapping subsets. We make the number of identities trained in the training process by combining multiple datasets. Un-

To summarize, our contributions include: (a) learning higher semantic and general features via a systematic framework and (b) getting competitive and efficient results comparing with state-of-the-art methods. Details are shown in experiments.

2. RELATED WORKS

2.1. Person re-ID using hand-crafted features

In the very beginning, people extract hand-crafted features to perform person re-ID. In [8], Farenzena et al. proposed the use of weighted color histogram, most stable color regions, and recurrent high-structured patches to extract person from an image. Gheissari et al. [9] proposed the use of HS histogram and edgel histogram within local regions to encode dominant local boundary orientation and RGB ratios for person re-ID. Besides the use of low-level features, middle-level features such as attribute-based features is also a possibility to use. In [10], Shi et al. proposed to learn attributes like color, texture, and category labels from fashion photography datasets.

2.2. Person re-ID using deep-learning-based

In contrast to the use of hand-crafted features for person re-ID, deep learning-based approaches adopt a completely different mechanism to handle the person re-ID problem. Li et al. [11] proposed the use of filter pairing neural network to handle misalignment, photometric and geometric transforms, occlusions, and cluttered background. In [4], Liu et al. tried to combine both soft attention and siamese model to ensure the focus is on the important parts of an input image pair. Cheng et al. [5] proposed a triplet function which examines three input images at the same time, a positive pair to learn similar relationship and a negative image to learn dissimilar relationship.

3. METHOD

In this section, we shall describe the details of the proposed method. The problem statement will be given first, followed by the introduction of hierarchical cross network. Then, how a combined dataset is formed will be introduced in Section 3.3. In section 3.4, a re-ranking strategy will be detailed.

3.1. Problem statement

Given a probe image (contains a person), the goal of person re-ID is to match his/her counterpart in the gallery set. A person re-ID process requires to handle both classification and retrieval simultaneously. Therefore, our system design must consider this requirement. In the training stage, suppose that a dataset has \( M \) identities with \( n \) images (\( M < n \)). Let \( D_i = \{x_i, d_i\} \) be the training set, where \( x_i \) denotes the \( i \)-th image and \( d_i \) denotes the identity covered in \( x_i \). Given an unknown probe image \( x \), we compute its feature representation \( f \) and compare \( f \) with the gallery set. Let the output of the comparison results be \( z = [z_1, z_2, ..., z_M] \in \mathbb{R}^M \). If we adopt Residual Network 50 (ResNet-50), the output \( z \) will be FC1000 layer and its dimension is not fixed. Usually, the dimension of \( z \) is equal to the number of identities covered in the training set. If the pool5 layer is adopted as feature representations, then its dimension is fixed. The cross entropy loss of identity classification can be formulated as \( L_{id}(f, d) = \sum_{m=1}^{M} - \log (p(m))q(m) \), where the predicted probability of each \( id \) is calculated as:

\[
 p(m|x) = \frac{\exp(z_m)}{\sum_{m'}\exp(z_{m'})},
\]

where \( q(y) = 1 \) if \( y \) is the ground truth and \( q(m) = 0 \) for \( m \neq y \).

In the testing stage, given a probe \( p \) and a gallery set with \( K \) images \( \{g_i\}_{i=1}^{K} \), identity is determined by

\[
d_p = \argmax_{i \in \{1, 2, ..., K\}} \text{sim}(q, g_i) \tag{1}
\]

, where \( d_p \) is the identity of probe \( p \) and the similarity between \( p \) and \( g_i \) can be measured by Mahalanobis distance \( \text{sim}(p, g_i) = (f_p - f_{g_i})\mathbf{M}^{-1}(f_p - f_{g_i}) \) where \( \mathbf{M} \) is a positive semidefinite matrix, \( f_p \) and \( f_{g_i} \) represent computed descriptors of probe \( p \) and gallery \( g_i \), respectively.

3.2. Hierarchical cross network

In this work, we use ResNet-50 [11] as the backbone of HCN. Although ResNet-50 has many residual blocks, we use the outputs of each stage’s last residual block \( \{R_2, R_3, R_4, R_5\} \) since these outputs have the strongest feature in each stage and we do not use conv1 since its semantically weak features do not bring better results.
There are a number of existing methods [5, 6, 7] that also exploit multiple layers to increase the semantic level of representations. We follow the concept proposed in Lin et al. [7] to construct the feature maps. These maps are obtained by merging upsampled, semantically stronger feature maps and the corresponding bottom-up feature maps through lateral connections. However, we do not consider to merge layers iterated from the coarsest to the finest since adjacent layers are strongly correlated. To obtain high semantic feature maps, merging these correlated adjacent layers iteratively is not the best choice since the merged maps have low diversity on semantic. In practice, we apply skip connections to merge layers which contain additionally a layer between them. Specifically, the hierarchical cross feature maps \( \{ C_1, C_2 \} \) do merge feature maps of backbone \( \{ R_3, R_5 \}, \{ R_2, R_4 \} \) by element-wise addition respectively.

Merging layers not only consider the height and the width of layers but also the depth of channel. In our work, we increase the capacity of HCN by extending channel dimensions of bottom-up maps to fit the channel dimensions of its corresponding top-down feature maps. Specifically, the depth of \( C_j \) and \( C_2 \) are different, which are 2048 and 1024 respectively. To reduce the overfitting of HCN, dropout layers are added before the predictions of hierarchical cross feature maps \( C_1, C_2 \) and the layer of backbone \( R_5 \). As the setting mentioned above, HCN finally has three outputs \( \{ R_5, C_1, C_2 \} \), we take the output of \( R_5 \) to be feature representations in experiments. The detailed procedure of an HCN-based person re-ID is shown in Figure 2.

3.3. Combined dataset

According to the setting of person re-ID, there are differences between training and probe images. Training images belong to one of the trained classes but probe images do not belong to any existing classes since they are usually “unseen”, i.e., \( d_x \in M, d_y \in K, M \cap K = \emptyset \), where \( d_x \) is the identity of training image \( x \).

As the above-mentioned situation, training multi-datasets jointly is feasible. Since the training dataset is disjoint with the probe images. Suppose we have \( D \) datasets, each dataset has \( M_i \) identities and \( N_i \) images. All training images are denoted as \( \{(x_{ij}, d_{ij})\}_{j=1}^{N_i} \) \( D \) \( i=1 \), where \( x_{ij} \) means the \( i \)-th image in the \( j \)-th dataset and \( d_{ij} \) denotes the identity of \( x_{ij} \) where \( d_{ij} \in \{1, 2, ..., M_i\} \). To avoid potential conflict on an id number, datasets are merged together into a combined dataset \( N = \sum_{i=1}^{D} N_i \) with new label \( d \in \{1, 2, ..., M\} \). This combined dataset which has \( M \) identities would be used in our framework during the training stage.

3.4. Re-ranking

Given a probe \( p \) and a gallery set with \( K \) images \( G = \{ g_i \}_{i=1}^{K} \), the initial ranking list \( L(p, G) = \{ g_1, g_2, ..., g_K \} \) is obtained according to the pairwise distance \( D_{p, g_i} = \sqrt{(f_p - f_{g_i})^2} \) where \( f_p \) and \( f_{g_i} \) are computed feature representations of probe \( p \) and gallery \( g_i \), respectively. Following [12], the \( k \)-reciprocal nearest neighbors \( R(p, k) \) can be defined as,

\[
R(p, k) = \{g_i | (g_i \in N(p, k)) \land (p \in N(g_i, k))\}
\]

(2)

where \( N(p, k) \) is the \( k \)-nearest neighbors of a probe \( p \),

\[
N(p, k) = \{n_1, n_2, ..., n_k\}, N(p, k) \subset G, |N(p, k)| = k
\]

(3)

To increase relevant images which are more similar than \( R(p, k) \) to probe \( p \), we follow [13] to add additional \( \frac{1}{2}k \)-reciprocal nearest neighbors to each \( R(p, k) \) to form \( R^+(p, k) \) and re-calculate the pairwise distance between the probe \( p \) and gallery \( g_i \) by combining both Euclidean and Jaccard distance [13],

\[
d(p, g_i) = (1 - \lambda)d_j(p, g_i) + \lambda d(p, g_i)
\]

(4)
where the Jaccard distance of the k-reciprocal set is defined as
\[
d_J(p, g_i) = 1 - \frac{|R^*(p, k) \cap R^*(g_i, k)|}{|R^*(p, k) \cup R^*(g_i, k)|}
\]
(5)

And $|\cdot|$ denotes the cardinality of the set. Methods mentioned above make ranking lists contain more hard positive images that can be used to increase performance.

## 4. EXPERIMENTS

### 4.1. Datasets and settings

Two large image-based datasets are adopted in experiments for closing to the realistic settings. Market-1501 [15] is currently the largest image-based dataset which is prepared by a university. It has 32,668 images which include 1501 identities that are detected by Deformable Part Model (DPM) [16]. The dataset is divided into two non-overlapping parts, 751 identities with 12,936 images and 750 identities with 19,732 images for training and testing respectively. The first set of experiments are conducted based on single-query inputs.

CUHK03 [17] is also a large scale image-based dataset which is formed by 14,096 images with 1467 identities. Among these identities, 767 are used for training and 700 are used for testing. Following the protocol [13], CUHK03 is split into two subsets which are CUHK03 labeled and CUHK03 detected based on the methods adopted for detecting person in images. Specifically, CUHK03 is manually labeled and CUHK03 detected is the formed by applying DPM. CUHK01 [18] is also an image-based dataset and its images are also captured in the same university. It is composed of 971 identities and we add all 971 identities to the combined dataset in the training stage for augmenting data. Details is shown in Table 1.

### 4.2. Evaluation protocol

Many datasets use Cumulated Matching Characteristics (CMC) curve to evaluate methods of person re-ID. A CMC curve is used to measure accuracy performance of methods that produce the rank list of possible matches and they usually turn out with the format of rankings. If there is only ground truth image for a given query image which is shown in Figure 4 (a), evaluations usually focus only on the precision rate, and under the circumstance the CMC curve is effective. However, if there are more than one ground truth images in response to a given query image shown in Figure 4 (b) and (c), then Mean Average Precision (mAP) is more appropriate for providing fair comparisons. In this case, both precision and recall have to be considered, and the precision of good methods will stay high as the recall rate increases. In this work, both Rank-1 and mAP are applied to evaluate the proposed methods.

### 4.3. Comparison with state-of-the-art methods

We first evaluate the performance of HCN and show the results in Table 2 and Table 3. HCN obtains better performance on Rank-1 and mAP than [13] on CUHK03 detected, CUHK03 labeled and Market-1501 datasets. To explore the effect of hierarchical feature maps on HCN, we compare the training loss of the prediction of $R_5$ between HCN and ResNet-50 in Figure 3. Under the same iteration, HCN has lower training loss than ResNet-50. This outcome indicates the effect of hierarchical feature maps on HCN, we compare the training loss of the prediction of $R_5$ between HCN and ResNet-50 in Figure 3. Under the same iteration, HCN has lower training loss than ResNet-50. This outcome indicates the hierarchical feature maps $\{C_1, C_2\}$ really help train better feature representations and also speed up the convergence rate.

We also compare our method (training HCN and combined dataset jointly) with state-of-the-art methods on CUHK03 labeled and CUHK03 detected datasets and show the results in Table 2. XQDA metric is shown since methods [13, 19] have the best rank-1 and mAP for this metric. In the CUHK03 detected dataset, our method gets 43.7% and 45.3% accuracy on rank-1 and mAP respectively, which gains more than 9% and 7.9% improvement compared with [13] methods. In the CUHK03 labeled dataset, our method obtains better results than previous methods, we have 44.0% gain for rank-1

| Datasets    | # ID | # Training ID | # Testing ID |
|-------------|------|---------------|--------------|
| Market-1501 | 1501 | 751           | 750          |
| CUHK03      | 1467 | 767           | 700          |
| CUHK01      | 971  | 971           | NaN          |
| Combined    | 2489 | 2489          | NaN          |

Table 1. The details of number of identities on datasets.

| Methods                              | CUHK03 detected | CUHK03 labeled |
|--------------------------------------|-----------------|----------------|
|                                      | Rank-1 | mAP  | Rank-1  | mAP  |
| LOMO+XQDA [19]                       | 16.6   | 17.8 | 19.1    | 20.8 |
| XQDA [13]                            | 31.1   | 28.2 | 32.0    | 29.6 |
| XQDA+re-rank [13]                    | 34.7   | 37.4 | 38.1    | 40.3 |
| HCN+re-rank                          | 40.9   | 43.0 | 43.4    | 46.0 |
| Ours+XQDA+re-rank                    | 43.7   | 45.3 | 44.0    | 46.9 |

Table 2. Comparison of previous methods with our results on CUHK03 detected and CUHK03 labeled datasets.

| Methods                              | Market-1501 |
|--------------------------------------|-------------|
|                                      | Rank-1 | mAP |
| SCSP [3]                             | 51.90   | 26.35 |
| DNS [20]                             | 61.02   | 35.68 |
| Gated [21]                           | 65.88   | 39.55 |
| ResNet50+Euclidean+re-rank [13]      | 81.44   | 70.39 |
| HCN+re-rank                          | 84.09   | 74.28 |
| Ours+re-rank                         | 82.63   | 72.66 |

Table 3. Comparison of previous methods with our results on Market-1501 dataset.
Fig. 3. Comparisons on training loss of $R_2$ between HCN and ResNet-50 (backbone) on datasets: (a) CUHK03 detected dataset. (b) CUHK03 labeled dataset. (c) Market-1501 dataset.

Table 4. Training time (hour) of Zhong [13] and our method on CUHK03 detected, CUHK03 labeled and Market-1501.

| Methods | detected | labeled | Market-1501 | Total |
|---------|----------|---------|-------------|-------|
| Zhong [13] | 36 | 36 | 24 | 96 |
| Our | 43 | 43 | |

and 46.9% gain for mAP.

When the experiments are conducted based on the Market-1501 dataset, the results shown in Table 5 are those obtained by our method and other state-of-the-art methods. It is clear that our method outperforms the methods proposed by [13], [20], [21] and [13]. Among the four state-of-the-art methods, the method that uses the combination of ResNet50+ Euclidean+ Re-rank [13] receives the best Rank-1 (81.44%) and mAP (70.39%). However, our method beats it in both the Rank-1 (82.63%) and mAP (72.66%) results. As to the effect of combined dataset, originally we expect to get better performance due to the potential of having more general feature representations. Unfortunately the received rank-1 and mAP results are both slightly lower than our HCN+ re-rank method we proposed in the Market-1501 dataset case. This result meets the hypothesis made in [22]. In [22], it was reported that a large domain helps a smaller domain dataset on learning, but would degrade the retrieval capability at the same time.

The advantage of using a combined dataset for training is to save the training time. In the experiments, the training time consumed on training different datasets are illustrated in Table 4. We use a Titan X GPU to run settings mentioned above and count the period between the start of training and the end of training according to its own log files. Costs on CUHK03 detected, CUHK03 labeled and Market-1501 datasets are about 36 hours, 36 hours and 24 hours respectively. Altogether, it costs almost 96 hours for finishing all trains. In our work, the combined dataset needs about 43 hours which is longer than individual datasets. However, to satisfy requirements in experiments, only one model is needed due to generalized features could be applied on cross datasets. Comparing with 96 hours, it saves more than 50% computation time.

In Figure 5 some experiment results on CUHK03 labeled are shown. Our method and the method of Zhong [13] are shown on the upper and the lower lists, respectively, for three different probe images.

5. CONCLUSIONS

Person re-ID is a challenging problem. To learn better feature representations, we applied HCN for learning high semantic features and combined dataset for making features being more general. Experiments show our method outperformed state-of-the-art methods. For future work, handling video-based person re-ID or person re-ID in a whole scene image will be interesting applications for us.
Fig. 5. Experiment results on CUHK03 labeled dataset. Images surrounded by green and red rectangles denote correct and incorrect matches, respectively.

6. REFERENCES

[1] Wei Li, Rui Zhao, Tong Xiao, and Xiaogang Wang, “Deepreid: Deep filter pairing neural network for person re-identification,” CVPR, 2014.

[2] Liang Zheng, Yi Yang, and Alexander G Hauptmann, “Person re-identification: Past, present and future,” arXiv preprint [arXiv:1610.02984], 2016.

[3] Dapeng Chen, Zejian Yuan, Badong Chen, and Nanning Zheng, “Similarity learning with spatial constraints for person re-identification,” CVPR, 2016.

[4] Hao Liu, Jiashi Feng, Meibin Qi, Jianguo Jiang, and Shuicheng Yan, “End-to-end comparative attention networks for person re-identification,” TIP, 2017.

[5] Bharath Hariharan, Pablo Arbeláez, Ross Girshick, and Jitendra Malik, “Hypercolumns for object segmentation and fine-grained localization,” CVPR, 2015.

[6] Jonathan Long, Evan Shelhamer, and Trevor Darrell, “Fully convolutional networks for semantic segmentation,” CVPR, 2015.

[7] Tsung-Yi Lin, Piotr Dollár, Ross Girshick, Kaiming He, Bharath Hariharan, and Serge Belongie, “Feature pyramid networks for object detection,” CVPR, 2017.

[8] Michela Farenzena, Loris Bazzani, Alessandro Perina, Vittorio Murino, and Marco Cristani, “Person re-identification by symmetry-driven accumulation of local features,” CVPR, 2010.

[9] Niloofar Gheissari, Thomas B Sebastian, and Richard Hartley, “Person reidentification using spatiotemporal appearance,” CVPR, 2006.

[10] Zhiyuan Shi, Timothy M Hospedales, and Tao Xiang, “Transferring a semantic representation for person re-identification and search,” CVPR, 2015.

[11] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, “Deep residual learning for image recognition,” CVPR, 2016.

[12] Danfeng Qin, Stephan Gammeter, Lukas Bossard, Till Quack, and Luc Van Gool, “Hello neighbor: Accurate object retrieval with k-reciprocal nearest neighbors,” CVPR, 2011.

[13] Zhun Zhong, Liang Zheng, Donglin Cao, and Shaozi Li, “Re-ranking person re-identification with k-reciprocal encoding,” CVPR, 2017.

[14] Paul Jaccard, “The distribution of the flora in the alpine zone,” New phytologist, vol. 11, no. 2, pp. 37–50, 1912.

[15] Liang Zheng, Liyue Shen, Lu Tian, Shengjin Wang, Jingdong Wang, and Qi Tian, “Scalable person re-identification: A benchmark,” ICCV, 2015.

[16] Pedro F Felzenszwalb, Ross B Girshick, David McAllester, and Deva Ramanan, “Object detection with discriminatively trained part-based models,” TPAMI, 2010.

[17] Wei Li, Rui Zhao, Tong Xiao, and Xiaogang Wang, “Deepreid: Deep filter pairing neural network for person re-identification,” CVPR, 2014.

[18] Wei Li and Xiaogang Wang, “Locally aligned feature transforms across views,” CVPR, 2013.

[19] Shengcai Liao, Yang Hu, Xiangyu Zhu, and Stan Z Li, “Person re-identification by local maximal occurrence representation and metric learning,” CVPR, 2015.

[20] Li Zhang, Tao Xiang, and Shaogang Gong, “Learning a discriminative null space for person re-identification,” CVPR, 2016.

[21] Rahul Rama Varior, Mrinal Haloi, and Gang Wang, “Gated siamese convolutional neural network architecture for human re-identification,” ECCV, 2016.

[22] Tong Xiao, Hongsheng Li, Wanli Ouyang, and Xiaogang Wang, “Learning deep feature representations with domain guided dropout for person re-identification,” CVPR, 2016.