A Comprehensive Study on Large-Scale Person Retrieval in Real Surveillance Scenarios

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Abstract

Person retrieval is a hot research topic due to its important application potential for public security. Though existing algorithms have achieved impressive progresses on current public datasets, it is still a challenging task in the real surveillance scenarios due to the various viewpoints, pose variations and occlusions. Moreover, few of the existing works study the problem of person retrieval on large-scale gallery set, where lots of distractions may deteriorate the retrieval results heavily. To have a deep understanding on the above challenges, we perform a comprehensive study on current state-of-the-art person retrieval algorithms with a large-scale benchmark in real surveillance scenarios. In the study, two kinds of techniques, i.e., attribute recognition and person re-identification, including eight algorithms, are evaluated at both algorithm level and system level. Here, the system-level evaluations investigate the effects of the combinations of the above algorithms with the module of person detection, where lots of distractions in person detection results pose a big challenge for person retrieval in real scenes. Extensive evaluations with large gallery sizes (up to 243k) and comprehensive analyses are presented in the study, which will guide researchers to develop more advanced algorithms in future.

1. Introduction

Person retrieval aims at searching the person(s) of interest from the captured large-scale surveillance image/video data with specific visual attributes or person images. It is an important application for public security, such as to find the criminal suspects and lost elderly or children. Depending on the different query conditions, person retrieval can be classified into the attribute-based retrieval and the image-based retrieval, in which attribute recognition and person re-identification (ReID) are the two core techniques.

Benefiting from the release of large-scale datasets, such as PA-100k \cite{23} and PETA \cite{4} for the attribute-based retrieval, Market1501 \cite{47} and DukeMTMC-reID \cite{28} for the image-based retrieval, and RAP \cite{17} for the both categories, as well as the success of deep learning models, the performance of person retrieval has been improved significantly. However, it is still a challenging task to obtain satisfying results in real surveillance scenes due to the large gallery size, low image quality, various viewpoints, large pose variations and occlusions. Though, these issues encourage the researchers to develop more robust algorithms, the main limitations of existing works can be summarized as follows.

First, existing works usually pay attention to improve the retrieval performances with a limited gallery size, few of them explore the influences of the large-scale gallery set with lots of distractions which is a common situation in real surveillance scenarios. These distractions may deteriorate the retrieval results heavily. The dataset of Market1501 \cite{47} provides a large-scale gallery set with 500k distractions. However, most of these distractions are easy samples, e.g. background, which do not accord with the real situations.

Second, the algorithms for attribute recognition and person ReID are often developed independently with self input-output definitions, train/test dataset and evaluation metrics. However, a real person retrieval system usually consists of several coherent vision algorithms, such as person detection and attribute recognition or person ReID. Therefore, its performance depends on all vision algorithms in the system execution pipeline. Some recent studies on person search \cite{41, 49, 39, 1} start to consider the person detection and ReID as a unified system. They are usually developed and evaluated on the datasets with both the person location and identity are annotated. However, the gallery size in real applications is always very large so that is hard to annotate all the samples in such large-scale gallery set. How to evaluate the performance with partial ground truth is still an open issue \cite{48}. Venetianer and Deng \cite{36} provide a fuzzy ground-truth based evaluation approach for both system-level and component-level evaluation. However, this work only showed a conceptual framework without practical test in a real system.
To have a deep understanding on the above problems, we perform a comprehensive study on current state-of-the-art person retrieval algorithms with a large-scale benchmark in real surveillance scenarios. These algorithms are collected from the Large-Scale Person Retrieval Challenge (LSPRC) which is held based on the proposed benchmark. In the study, two kinds of techniques, i.e., attribute recognition and person ReID, totally eight algorithms, are evaluated at both algorithm level and system level. Different from the existing works, the system-level evaluations investigate the effects of the combinations of the above algorithms with the module of person detection, where lots of distractions in person detection results pose a big challenge in person retrieval in real scenes. Thus, the contributions of this paper include following aspects:

- We present a large-scale benchmark for person retrieval in real surveillance scenarios with standard dataset and metrics, in which the dataset is a subset of RAP [17] and is named RAP-LSPRC in this paper.
- We propose a system-level evaluation paradigm to measure the retrieval performance through combining the algorithms for attributes recognition or ReID with the real person detector as a unified system so that the effects of lots of detected distractions are considered.
- We give a comprehensive study for eight state-of-the-art person retrieval algorithms, which are the submissions in LSPRC, on the proposed benchmark. The results of the extensive evaluations will guide researchers to develop more advanced algorithms in future.

The remainder of this paper is organized as follows: Section 2 reviews the related work. Section 3 introduces the proposed benchmark. Section 4 overviews the eight algorithms submitted to LSPRC. Section 5 shows the experimental results and corresponding analysis. Finally, we conclude this work in Section 6.

2. Related Work

2.1. Overview on Person Retrieval

For the attribute-based person retrieval, modern methods are usually developed with the Deep Convolutional Neural Network (DCNN) [32, 14, 16], Recurrent Neural Network (RNN) [38], and attention model [23] etc. And some of them improve the performance through exploring the human pose information [16] or the context information among attributes [38, 23].

For the image-based person retrieval, representation learning and metric learning are the two core research contents. To learn robust representation, many efforts mainly focus on alleviating the problem of misalignment across different viewpoints. In [33, 37], the person image is partitioned into several rigid horizontal stripes to learn the local features. Some other work learns the aligned deep features using human parts [15, 46], pose [31], mask [30, 13], or even dense semantic alignment of the human body [45]. For the metric learning, to keep the features of the same identity closer while push the features of different identities further apart, modern methods [3, 37] usually utilize both the classification loss and ranking loss to optimize the network.

Though the performances of these methods have achieved much progress on current public datasets, most of them only consider the gallery set with predefined bounding boxes. While these bounding boxes are usually generated by person detectors in the real applications. Meanwhile, few of the above methods take the impacts of large-scale gallery set with lots of distractions into account.

The task of person search, which is first proposed in [41], turns to consider the person detection and ReID as a coherent system. Some work [39, 22] jointly learns detection and identification features in an end-to-end manner; others [49, 1] optimize the detection and ReID separately. Different from the work of common person ReID and person search, open-world person ReID [20, 50, 53, 19] studies the person verification problem, in which not all the query identities are appeared in the gallery set. Though the tasks of person search and open-world ReID are close to the real applications, neither of them proposes a proper evaluation metric when only partial samples in the large-scale gallery set are annotated.

2.2. Related Benchmarks And Challenges

Benchmarks. The large-scale annotated datasets with standard evaluation metrics play an important role to develop robust algorithms. APiS [52], PETA [4] and PA-100k [23] are three popular datasets for attribute recognition. They are collected with different number of samples and kinds of attributes. CUHK03 [18], Market1501 [47] and DukeMTMC-ReID [28] are the three most popular datasets for person ReID. They are collected with different number of identities across multiple cameras in various scenes. However, all of these datasets only consider the samples with pre-defined bounding boxes. CUHK-SYSU [39] and PRW [49] are two datasets for person search, in which both the person location and identity are annotated. Thus, the effects of person detection can be considered when developing and evaluating the algorithms for person ReID. However, it is much labor-intensive to annotate such large-scale datasets.

Challenges. The related challenges also promote the researchers to improve the performances of corresponding algorithms. The challenge of Semantic Person Retrieval in Surveillance Using Soft Biometrics [7] is run in AVSS 2018, whose purpose is to locate the interesting target with the semantic attributes. It only released a small size of data to the participants. The person search track in WIDER Challenge [25] is another challenge for person retrieval held in ECCV 2018, which is to search a given portrait from can-
3. Proposed Benchmark

3.1. Dataset

A subset of samples is selected from the richly annotated pedestrian (RAP) dataset [17] to construct the proposed benchmark which includes more than 68 thousands pedestrian images annotated with 72 fine-grade attributes and 2,589 identities (IDs). It is named RAP-LSPRC in this paper. Some basic information is listed in Table 1. And several samples in RAP-LSPRC are shown in Fig. 1.

Moreover, 39,278 complete frames corresponding to the test sets for attribute recognition and person ReID are also provided to execute system-level evaluation where a person detection algorithm is firstly perform to construct a large-scale gallery set. Thus, lots of detection results in the gallery set would act as distractions.

3.2. Tasks

Based on the different querying conditions, two kinds of tasks, i.e., attribute-based person retrieval (PR-A) and image-based person retrieval (PR-ID), are considered in the proposed benchmark.

3.2.1 Task of PR-A

The task of PR-A is to search the interesting person with one or multiple attributes. To complete this task, attribute recognition is utilized to obtain the likelihoods of predefined attributes which are further used to calculate the ranking list. PR-A consists of two stages, i.e., PR-A-RAP and PR-A-SYS, based on the two kinds of evaluation metrics.

PR-A-RAP. A list of query conditions are generated with different number of attributes (ranging from 1 to 4). Under different query conditions, the samples in the gallery set are ranked with the likelihoods of desirable attributes. And the ranking results are further evaluated using the ground truth which is provided in the RAP-LSPRC dataset.

PR-A-SYS. Different pipelines (algorithm combination) are generated through combing the algorithms for attribute recognition with a specific person detector. The complete frames, which are corresponding to the gallery set, are parsed with these pipelines. Inspired by the work [6] and [26], a question-answering (QA) paradigm is designed to evaluate the performance of person retrieval system. As shown in Table 2, more than 5 million polar (binary) queries (whether a person with the specified attribute(s)) are generated based on the ground truth of the test set in RAP-LSPRC. The performances of the QA results reflect the performances of the submitted algorithms integrated into the person retrieval system.

3.2.2 Task of PR-ID

The task of PR-ID is to search the interesting person through measuring the similarities between its ReID features and those of the samples in gallery set. The Euclidean distance is restricted to measure the similarities. And then these similarities are used to generate the ranking list. Similar to the task of PR-A, it also consists of two stages, i.e., PR-ID-RAP and PR-ID-SYS, based on the two kinds of evaluation metrics.

PR-ID-RAP. A subset of samples in the test set is selected as the query set; the others are selected as gallery set. For each image in the query set, the similarities with all the images in the gallery set are calculated based on the ReID features. Then, sort all the images in the gallery set descending with the similarities to generate the ranking list. The ranking results are also evaluated using the ground truth which is provided in the RAP-LSPRC dataset.

PR-ID-SYS. Similar with PR-A-SYS, the algorithms for ReID are combined with a specific person detector to generate different pipelines. The complete frames corresponding to both the query and gallery set in RAP-LSPRC are parsed with these pipelines. Then, the kNN-search is conducted for all the detected persons to get their top-k (k is set to 100 in this paper) neighbours using ReID features. A relationship graph is constructed with the results of kNN-search, where each node represents a person, and the edge reflects if the two nodes belong to the same ID. Meanwhile, more than 17 million polar queries (whether the two persons with the same ID or not) are generated based on the ground truth of the test set in RAP-LSPRC (see Table 2). They are used to measure the performance of the person retrieval system.

3.3. Evaluation Metrics

Two kinds of evaluations, i.e., algorithm-level evaluation and system-level evaluation, are adopted in this benchmark.

3.3.1 Algorithm-Level Evaluation

Given a query image or condition with different attributes, a ranking list is generated with the similarities/likelihoods which are calculated using the trained models. Thus, the
The mean average precision (mAP) is utilized to evaluate the performances of the two kinds of tasks. For a query, the average precision (AP) is defined in Eq. 1.

\[
AP = \frac{\sum_{r=1}^{N} P(r) \times \mathbb{1}(r)}{K}
\]

where \(N\) is the number of samples in the gallery set; \(P(r)\) is the precision at rank \(r\); \(\mathbb{1}(r)\) is an indicator function that represents whether the sample at rank \(r\) is related to current query; and \(K\) is the number of related samples. The mAP is further calculated through averaging all the values of AP under different query conditions. It is worth noting that only the samples locating in the different cameras with the query image are considered in Eq. 1.

### 3.3.2 System-Level Evaluation

For the system-level evaluations, the Faster-RCNN [27] is chosen as the default person detector to combine with the algorithms for attribute recognition or person ReID, in which the threshold of Intersection over Union (IoU) is set to 0.5 (IoU>0.5). Thus, a large-scale gallery set including 243,353 samples are collected, in which only partial samples are annotated and lots of distractions are included. To evaluate the person retrieval system with such a gallery set, we adopt a QA paradigm which is inspired by two work.

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The Large-Scale Person Retrieval Challenge (LSPRC) is held based on the proposed benchmark, to which more than fifteen valid algorithms are submitted. In this paper, eight representative algorithms of them are selected to have a comprehensive study.

All the submissions for the LSPRC are restricted to train without using extra data. And the data in RAP-LSPRC for one task can NOT be utilized to another as well.

### 4. Methods

The Large-Scale Person Retrieval Challenge (LSPRC) is held based on the proposed benchmark, to which more than fifteen valid algorithms are submitted. In this paper, eight representative algorithms of them are selected to have a comprehensive study.

#### 4.1. Attribute Recognition Methods

Attribute recognition is the core technique for the task of PR-A. This section summarizes the top-3 submissions for this task (see Table. 3). From the submissions, we can find that all of them are based on deep architecture with different backbone networks and loss functions. Meanwhile, we can also find that the attention mechanism and learning the context information among different attributes are two popular methods to improve the performance.

#### 4.2. Person ReID Methods

Person ReID is the core technique for the task of PR-ID. This section shows an overview on the top-5 submissions (see Table. 4). The deep learning based methods dominate this field as well. The characteristics of the top-5 submissions can be summarized as follows: 1) the ResNet [8] and DenseNet [11] with various numbers of layers are the most two popular networks that are utilized as the backbone; 2) multi-model fusion is widely used to generate the final features through concatenating the output of each model; 3) MGN [37] is a popular framework that are utilized to capture both the global and local features; 4) the feature maps from different layers are considered in some of the submissions to capture more information of different levels; 5)
Table 3. A summary on the top-3 submissions of task PR-A.

<table>
<thead>
<tr>
<th>Submissions</th>
<th>Characteristics</th>
<th>Multi-model Fusion (# Models)</th>
<th>Backbone Network</th>
<th>Loss Function</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2. Input images are resized to 128 × 256.</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>3. Data augmentation: random rotation and cropping.</td>
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<td></td>
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<tr>
<td></td>
<td>4. The initial learning rate is 0.01 which is updated with SGDR [22].</td>
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<td></td>
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<tr>
<td>2</td>
<td>1. Design a network including four separate branches; and each branch is responsible for partial attributes.</td>
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<td></td>
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<tr>
<td></td>
<td>4. The input images are resized to 224 × 224 × 3.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1. Propose a network which consists of three components: Main Net, View Prediction Net (VPN) [29] and Spatial Regularization Net (SRN) [51].</td>
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<td></td>
<td></td>
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<tr>
<td></td>
<td>2. The VPN is trained to classify the viewpoints (front, back and side).</td>
<td>No</td>
<td>GoogleNet Inception [35]</td>
<td>Cross-Entropy Loss</td>
</tr>
<tr>
<td></td>
<td>3. The SRN is utilized to learn the spatial context information among different attributes.</td>
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<tr>
<td></td>
<td>4. Main Net predicts the attributes from three viewpoints respectively, in which the outputs are weighted by the results of VPN; and it is further aggregated with the results of SRN to generate the final predictions.</td>
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</tr>
</tbody>
</table>

Table 5. The numbers of positives in the top-100 for 100 randomly selected query person images. The average number is 23.74.

Table 6. The evaluation results of the top-3 submissions of PR-A.

<table>
<thead>
<tr>
<th>Methods</th>
<th>mAP (PR-A-RAP)</th>
<th>P30 score (PR-A-SYS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.4220</td>
<td>0.4135</td>
</tr>
<tr>
<td>2</td>
<td>0.4107</td>
<td>0.2042</td>
</tr>
<tr>
<td>3</td>
<td>0.3512</td>
<td>0.2435</td>
</tr>
</tbody>
</table>

5. Experimental Results

5.1. Setups

For the task of PR-A, 205 query conditions are generated with 54 attributes which involve gender, age, clothing, action and etc. The number of attributes for one query condition is ranging from 1 to 4. And we choose 0.5 as the classification threshold.

For the task of PR-ID, 7,202 query person images are randomly selected from the test set as shown in Table 1. And to count the number of true positives and false positives in PR-ID-SYS, the values of $r_p$ and $r_n$ in Eq. 6 are set to 100 and 10 respectively. The two thresholds are determined based on a hypothesis that the numbers of positives in the large-scale gallery set for most query person images are far less than 100. To verify its validity, 100 query person images are randomly selected to check the ranking results with the detected gallery set whose size is more than 243k. The statistical result is shown in Table 5. We can find that the count of query images, whose number of positives is larger than 80 in top-100, is only 7 (%7). It indicates the validity of the hypothesis.

Figure 2. Number of true positives in rank-100 under different gallery size. (a)∼(d) show the changing trends with different number of attributes.

ResNet and submission-2 with DenseNet vs. submission-3 with GoogleNet) incline to generate superior performances (mAP) on the test set with predefined bounding boxes. And the data unbalance of different attributes is considered by using of focal loss in submission-1, which improves the performance further and makes it the first place.

System-Level Evaluation. The last column of Table 6 shows the evaluation results of PR-A-SYS about the top-3 submissions. The lower quality of the detected samples, such as the parts missing and position shifting in the bounding box, makes them much harder to recognize than the ideal samples. So the strategies, such as attention mechanism and learning the context information among different attributes, play the key role to improve the performance ($F_3$). It leads the results of submission-3 superior to that of submission-2. Meanwhile, the effect of different gallery sizes on the ranking results is also studied. We count the number of true positives in the rank-100. The statistical re-
results with different number of attributes are shown in Fig. 2. They are consistent with the expectations that the number of true positives decreases along with the increasing of gallery size as more distractions occupy the places in the rank-100. We can also find that the decline of submission-1 is more obvious than the other two methods. It is the higher recall (0.4889 for submission-1 vs. 0.1592 for submission-2 and 0.2045 for submission-3) and lower precision (0.3792 for submission-1 vs. 0.6080 for submission-2 and 0.4855 for submission-3) of submission-1 makes this method is prone to pull the distractions into rank-100.

5.3. Results of PR-ID

Algorithm-Level Evaluation. The second column of Table 7 lists the evaluation results of PR-ID-RAP about the top-5 submissions. Except for the submission-5 in the 5th place, the multi-model fusion is utilized by all the other four submissions. And the number of models increases from the 4th place to the 1st place (3 to 5). Moreover, the backbone network becomes more complicated as higher ranking performance, e.g. SEResNet152, ResNet152 and DenseNet201 are used by submission-1 in the 1st place. The two folds indicate that the complicated frameworks cline to achieve better performance (mAP).

System-Level Evaluation. The last column of Table 7 lists the evaluation results of PR-ID-SYS about the top-5 submissions. It obtains the similar ranking with PR-ID-RAP except that the performance of submission-5 exceeds the result of submission-4. Comparing their frameworks, we can find that all of them are based on the MGN [37].

![Table 4](image)

![Table 7](image)

![Figure 3](image)
enlarging of gallery set. It is mainly because more distractions occupy the places in top-\(r_p\). Thus fewer true positives can appear at those positions. It is the same reason that fewer false positives can locate in the top-\(r_n\), which improve the value of precision (see Fig. 3(a)). However, the decline of the recall is more significant than the improvement of the precision. It results in the decline of \(F_1\) scores finally.

5.4. Discussion

From the overview of the submissions (Sec. 4) and the experimental results, we can conclude as follows:

- The deep learning based methods dominate the field of person retrieval that the ResNet [8] and DenseNet [11] are the most two popular networks utilized as the backbone.

- The complicated frameworks, such as multi-model fusion with complex backbone networks, are tend to achieve superior performance.

- For the task of PR-A, the attention mechanism and learning the context information among different attributes are two effective methods to improve the performance, especially under the gallery set collected by pedestrian detectors.

- For the task of PR-ID, MGN [37] based frameworks can concentrate on both the global and local discriminative clues which contribute to generate superior performance especially under the system-level evaluation.

- As the introducing of distractions to the gallery set, it leads to heavily negative effect on the ranking results on both tasks. So the person retrieval is still a challenging issue under real scenarios.

6. Conclusion

This paper proposed a large-scale benchmark for person retrieval in real surveillance scenarios, in which the attribute recognition and person ReID are included. Different from the existing works, besides the common algorithm-level evaluation on closed set, the system-level evaluations are introduced to measure the algorithms combing with the coherent person detector, where the detected pedestrians constitute the large-scale gallery set and only some of them are annotated. Thus, it could reflect the performance under the real scenarios. We also give a comprehensive study for the impacts of various gallery sizes on the performance of the person retrieval system using the proposed metrics. The results indicate that person retrieval in real scenarios is still an intractable issue as lots of distractions exist in the gallery set. In future work, facing the large-scale gallery set, we will introduce a new evaluation mechanism based on “human-in-the-loop” to adopt users feedbacks to evaluate the system performance.

Acknowledgements. This work is sponsored by National Key Research and Development Program of China (2016YFB1001002) and CAS-AIR.

References


