

# Large-Scale Pedestrian Retrieval Competition

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## 1 Overview and Motivation

The Large-Scale Pedestrian Retrieval Competition (LSPRC) mainly focuses on person retrieval which is an important end application in intelligent vision system of surveillance. Person retrieval aims at searching the interested target with specific visual attributes or images. The low image quality, various camera viewpoints, large pose variations and occlusions in real scenes make it a challenge problem.

By providing large-scale surveillance data in real scene and standard evaluation methods that are closer to real application, the competition aims to improve the robust of related algorithms and further meet the complicated situations in real application. LSPRC includes two kinds of tasks, i.e., Attribute based Pedestrian Retrieval (PR-A) and Re-IDentification (ReID) based Pedestrian Retrieval (PR-ID). The normal evaluation index, i.e., mean Average Precision (mAP), is used to measure the performances of the two tasks under various scale, pose and occlusion. While the method of system evaluation is introduced to evaluate the person retrieval system in which the related algorithms of the two tasks are integrated into a large-scale video parsing platform (named ISEE) combining with algorithm of pedestrian detection.

The competition is hold in Chinese Conference on Pattern Recognition and Computer Vision in 2018 (PRCV2018)<sup>1</sup> and attract more than thirty institutions to participate. This report gives a brief analysis and conclusion on the competition results which may help researchers to develop more robust algorithms.

## 2 Dataset

A richly annotated pedestrian (RAP) dataset [7], which is collected for person retrieval in real visual surveillance scenarios, is adopted in LSPRC. A subset of samples is selected from RAP in this competition, which includes more than 68 thousands pedestrian images annotated with 72 fine-grade attributes and 2,589 identities (IDs). These samples are split into three parts, i.e., training, test and validation. Some basic information is listed in Table 1. And several samples in RAP are shown in Fig. 1.

Besides the annotated RAP dataset, about 350 hours(h) raw HD videos corresponding to the labeled image samples are also provided for the system evaluations on the performances of Atributes-based or Re-Identification (ReID)-based pedestrian retrieval.

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<sup>1</sup> <http://prcv.qyhw.net.cn/>

**Table 1.** Basic information of the data used in LSPRC.

Attribute				Re-Identification		Other Information	
#Training Samples	#Validation Samples	#Test Samples	#Attributes	#Training IDs (samples)	#Test IDs (samples)	Resolution ( $w \times h$ )	# Cameras
33268	8317	25986	72	1295 (13178)	1294 13460	from $33 \times 81$ to $415 \times 583$	25

**Fig. 1.** Image samples in RAP. In real scene, attributes change a lot due to camera viewpoint, body part occlusion, human pose, time range, and image quality, etc. These make the person retrieval a challenging problem.

Moreover, another subset of whole image samples in RAP, which are annotated with pedestrian bounding boxes, are provided to train the person detection model that can be combined with subsequent recognition algorithms in the stage of system evaluation.

### 3 Tasks

Based on the different querying conditions, LSPRC includes two kinds of tasks, i.e., Attribute-based Pedestrian Retrieval (PR-A) and ReID-based Pedestrian Retrieval (PR-ID).

#### 3.1 Task of PR-A

The task of PR-A in LSPRC can be seen as analogous to Attribute Recognition. The confidence scores of existed attributes are the basis for further retrieval. It worth to note that the model is employed to PR-A can only be trained with the training set in RAP.

PR-A can be divided into two stage based on the two kinds of evaluation methods, i.e., PR-A-RAP and PR-A-SYS.

**PR-A-RAP.** A list of query conditions are generated with different number of attributes (ranging from 1 to 4). Under different conditions, search the samples in test set based on the confidence scores which are obtained through attribute recognition.

**PR-A-SYS.** In this stage, different pipelines, through combing the submitted algorithms of attribute recognition with pedestrian detection, are generate to parse the 100h videos on ISEE. Meanwhile, inspired by the works [3] and [8], 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 test set in RAP. The performance of the question-answering results reflect the performance of submitted algorithm integrated into the person retrieval system.

### 3.2 Task of PR-ID

The task of PR-A in LSPRC can be seen as analogous to person ReID. The trained ReID model is used to extract features for both the probe and gallery images. The features are further used to calculate the similarity between the probe and gallery image. PR-ID can be divided into two stage as well, i.e., PR-ID-RAP and PR-ID-SYS. No other auxiliary data related to person ReID is allowed in training.

**PR-ID-RAP.** A subset of samples in the test set is selected as the query set. Then, for each image in the query set, calculate the similarity with all the images in test set based on the ReID features. Sort all the images in test set descending depended on the similarity which is the basis to determine if the two samples the same ID or not.

**PR-ID-SYS.** Similar with PR-A-SYS, the submitted algorithms for ReID are combined with pedestrian detection to generate different pipelines to parse another 250h videos on ISEE. Then, the KNN-search is conducted for all the detected pedestrians to get their top-K neighbours using ReID features. A relationship graph is further 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 15 million polar queries (whether the two pedestrians with the same ID or not) are generated based on the ground truth of test set in RAP (see Table 2). The performance of the question-answering results reflect the performance of submitted algorithm integrated into the person retrieval system.

**Table 2.** Number of queries used in PR-A-SYS and PR-ID-SYS.

PR-A-SYS		PR-ID-SYS	
# Positive Queries	# Negative Queries	# Positive Queries	# Negative Queries
354,700	4,972,430	491,518	15,723,652

## 4 Evaluation

More than fifteen valid models about the two tasks are submitted finally. The evaluation results of PR-A are list in Table 3, in which DeepMAR [5] is the baseline model which is fine-tuned with the training data provided by LSPRC. We can find that the performances of the champion model on both PR-A-RAP

and PR-A-SYS are inferior to those of the baseline method. It indicates that the task of attribute recognition is still a challenge problem in real surveillance scenes.

**Table 3.** The evaluation results of PR-A.

Team	Method	mAP (PR-A-RAP)	$F_1$ score (PR-A-SYS)
Deeplning	Modify the conv-layer in the attention module of [9] with deformable convolution [2].	<b>0.4220</b>	<b>0.4135</b>
ASTRI	Densenet (Backbone) for features extraction; another four branches for attributes prediction.	0.4107	0.2042
Xiangtan University	VPN[10]; train a classifier for view point; SRN[14]; learn the multi-label relations among images.	0.3512	0.2455
TYUT	Xception [1]	0.0777	0.0019
DeepMAR [5]	Multi-label classification with ResNet50.	0.4267	0.4196

Table 4 shows the evaluation results on PR-ID. MSCAN [6] listed in the last row is the baseline method. The value of its performance (mAP) is copied from the original paper directly. And we also did not evaluate it in the stage of PR-ID-SYS. Different from the results in PR-A, most of the submitted models achieve superior performance than baseline method on PR-ID-RAP. Moreover, from the column of *Method*, we can find that multi-model fusion and part-based model are two common strategy to improve the performances of PR-ID.

**Table 4.** The evaluation results of PR-ID.

Team	Method	mAP (PR-ID-RAP)	$F_1$ score (PR-ID-SYS)
Dahua Technology	Multi-model fusion: PCB [11] & MGN [12] Backbone: seresnet152, resnet152, densenet201	<b>0.7335</b>	<b>0.5286</b>
SYSU & ZNV Technology	Multi-model fusion: PCB [11] & MGN [12] Backbone: resnet101, senet50, densenet129	0.7087	0.5263
Weihua Chen	Multi-model fusion & human parsing assistant; Local feature learning: PCB [11] & MGN [12]; Global feature learning: midfeat [13]	0.6421	0.5030
The Army Engineering University of PLA	Multi-model fusion	0.6059	0.4802
DiDi Research	MGN [12]	0.5933	0.4906
ZJU & ZJUT & iCareVision	-	0.5182	0.4629
Wave Kingdom	-	0.4984	0.3862
deeplning	-	0.4601	0.3844
China University of Petroleum	-	0.4542	0.3852
SYSU-NSCC	-	0.4492	0.4108
ASTRI	-	0.3951	0.3242
TYUT	-	0.1461	0.1618
Anhui University	-	-	0.2393
GDUT	-	-	0.1375
MSCAN [6]	Cut the pedestrian image into several parts softly.	0.3828	-

## 5 Conclusion

In this report, we introduced the Large-Scale Pedestrian Retrieval Competition (LSPRC) including the dataset, tasks and evaluation results. From the results, we can summarize as follows.

- The best performances of the two tasks are lower than 60%, which are not satisfying for real applications. So person retrieval is still a challenge problem.
- For the task of PR-ID, multi-model fusion and part-based model are the most common strategies in submitted methods. Especially, the local features can be extracted through the part-based model, which provide more fine-grained information about spatial alignment. So the methods, such as DensePose [4], which can provide more precision information on alignment, have attracted extensive attention on developing modern ReID models.

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