Vehicle Re-identification Method Based on Vehicle Attribute and Mutual Exclusion Between Cameras

Junru Chen\textsuperscript{1}, Shiqing Geng\textsuperscript{2}, Yongluan Yan\textsuperscript{3}, Danyang Huang\textsuperscript{4}, Hao Liu\textsuperscript{4}, Yadong Li\textsuperscript{4}

Xidian University\textsuperscript{1}
Harbin Engineering University\textsuperscript{2}
Huazhong University of Science and Technology\textsuperscript{3}
Beihang University\textsuperscript{4}

Abstract

Vehicle Re-identification aims to identify a specific vehicle across time and camera view. With the rapid growth of intelligent transportation systems and smart cities, vehicle Re-identification technology gets more and more attention. However, due to the difference of shooting angle and the high similarity of vehicles belonging to the same brand, vehicle re-identification becomes a great challenge for existing method \cite{22}. In this paper, we propose a vehicle attribute-guided method to re-rank vehicle Re-ID result. The attributes used include vehicle orientation and vehicle brand. We also focus on the camera information and introduce camera mutual exclusion theory to further fine-tune the search results. In terms of feature extraction, we combine the data augmentations of multi-resolutions with the large model ensemble to get a more robust vehicle features. Our method achieves mAP of 63.73\% and rank-1 accuracy 76.61\% in the CVPR 2021 AI City Challenge.

1. Introduction

Given a query vehicle image, vehicle re-identification (Re-ID) aims to find the matched vehicle from a gallery of vehicle images. Most of existing methods use Convolutional Neural Network (CNN) \cite{18, 26, 32} to extract features of vehicle images and compute the distance between features to get a rank list of similarity between the query image and gallery images. Though many existing Re-ID methods \cite{33, 31, 11, 10} achieve great results, there are still several challenges in the Re-ID task of the city surveillance scene.

One of the challenges is that the appearance of two images captured by different cameras could be quite different even though they belong to the same vehicle. The big difference of images belonging to the same vehicle comes from the difference of illumination and vehicle orientation.

We mainly focus on vehicle orientation in this paper. We introduce a vehicle orientation model to predict the vehicle orientation (0-360 degrees). For the images of vehicles with large angle difference, we subtract a value from their distance to make them closer in embedding space, so as to improve the accuracy of model prediction. Since appearance features of the vehicles facing forward and those facing backward are similar, we propose to a folding operation of the angle, which regards the forward and backward as the same orientation.

Another challenge is that the appearance of some vehicles with the same brand and same type could be quite close. Thus we introduce a coarse vehicle classification model for predicting the type of vehicles and a vehicle main brand prediction model to assist the vehicle Re-ID task.

In addition to using traditional re-rank methods \cite{30, 28}, we also introduce a re-rank method based on the mutual exclusion of camera location. Through observation, we found that the same vehicle does not appear in the same camera twice. Therefore, when finding matched gallery image for a query image according to the rank list of similarity, if a image belonging to a certain camera has been retrieved, we
move other images captured by this camera to the back of rank list. In other words, we reduce the similarity between the query image and other images belonging to the retrieved camera.

Besides, another challenge in AI City Challenge is that there are many blurred images in the test dataset, which makes the model difficult to distinguish images. To address above issue, we combine four models with same architecture and different input image size. In this way, the whole network can adapt to images of different resolutions, which is equivalent to both clear and blurred images. And the real-word training dataset also has the problem of inaccurate detection bounding box, so we re-detect those images and crop them for reducing the influence of background information, as shown in Figure 1.

In this paper, our proposed methods mainly focus on how to use large models to extract more robust features, the general architecture is shown in Figure 2, and use vehicle orientation and vehicle brand information to fine-tune the original ranking result. In summary, our contributions are:

- We propose a method utilizing vehicle orientation and brand information for vehicle ReID.
- We train the model with multi-scale images and reduce the background area of images using vehicle detection to improve the robustness of model since the quality of images is largely different.
- We propose a camera mutual exclusion theory which combines the query/gallery camera id to fine-tune final retrieval result.
- Our vehicle ReID method achieves mAP of 63.73% and rank-1 accuracy 76.61% in the CVPR 2021 AI City Challenge.

2. Related Work

With the rapid development of convolutional neural networks (CNNs) [6, 9, 16, 27], vehicle re-identification has made great achievements in recent years. [13] proposed DRDL to map vehicle images into an Euclidean space and used the L2 distance between two images for similarity estimation. [14] combined a Region branch which encourages the deep model to learn more local information and thus get more discriminative features.

Similar to person re-identification [29, 20] and face recognition [24, 17], vehicle re-identification also aims to learn a feature space which keeps the samples from the same class close to each other and those from different classes far away via some effective deep metric loss. The commonly used loss functions include Cosface [24], Circle Loss [19], Triplet Loss [17]. However, there are two main challenges of vehicle ReID: large intra-class difference and small inter-class similarity due to the viewpoints, cameras, illumination and other factors. Many recent vehicle ReID works have focused on learning a robust feature with vehicle attributes, vehicle orientation, vehicle keypoints and etc. [2] considered the viewpoint variation problem in vehicle ReID, and proposed a VANet that learns two metrics of similar viewpoints and different viewpoints in two feature spaces. [5] introduced a part-regularized ReID approach that uses a part-localization network to detect ROIs (Region of interest) and then projects the ROIs into the global feature map to learn part features and distinguish the subtle discrepancy. In [25], it combines more local region features by presenting 20 fixed key points for vehicle. [23] proposed AGNet with attribute-guided attention module which makes full use of vehicle attributes to distinguish different vehicles.

Recently, many transformer-based methods [4, 3, 12]
Figure 3. Testing pipeline. First, the original picture will go through a detection model to obtain the image after removing the redundant background. Send both types of images into 12 feature extractors to get 24 similarity matrices. Re-ranking and adding the matrices to get the ensembled results, filtered by the camera id, vehicle orientation, vehicle brand and vehicle type to adjust the similarity matrix. Merge the results of the vehicles which from the same track, those images is inserted behind the top-ranked one. Then use the camera mutual exclusion strategy to get the final search result.

have been verified in the visual task. In Re-ID task, there is also a purely transformer based method [8, 32], and it achieves even better performance than CNN-based methods on some human and vehicle re-identification benchmarks.

3. Method

In order to get better retrieval results, we have adopted two types of processing methods, one type of methods are some general approaches for improving the results of vehicle re-identification, the other type of methods are relatively tricky and aim to improve the performance on AI City Challenge. The general methods include re-ranking, model ensemble, and combining additional vehicle information such as vehicle type, brand, orientation to fine-tune results. The tricky methods include filtering the images of the same camera in gallery, merging the results of the vehicles that from the same track, re-ranking based on mutual exclusion between cameras, etc. The flow chart of the entire testing pipeline is shown in Figure 3.

3.1. Data Preprocessing

We find that the background area of some images in the CityFlow [21] dataset is too large. Therefore, we pass all the training set and test set images through the detection model to obtain new images for training and testing, experimental results shows that the using new detected images can achieve better performance than using the original images.

3.2. Loss Function

We adopt triplet loss and Cosface loss jointly to optimize the model. The purpose of Cosface loss is to convert the absolute distance of vectors in the euclidean space into the relative distance of the angle between the two vectors in the cosine space. The Cosface loss is computed as:

$$L_{id} = \frac{1}{N} \sum_i -\log e^{s(\cos(\theta_{y_i,i})-m)} + \sum_{j \neq y_i} e^{s\cos(\theta_{j,i})}$$

, where $m$ refers to margin of the cosine distance, $s$ means the scale of vectors. In experiment, $m$ is set to 0.35 and $s$ is set to 30.

The purpose of triplet loss is to reduce the distance between the features of same vehicles and expand the distance between the features of different vehicles. Triplet loss is computed as:

$$L_{triplet} = [d_p - d_n + \alpha]_+$$

, where $d_p$ and $d_n$ are the distance of positive pairs and negative pairs in the feature space respectively, $\alpha$ is the margin of triplet loss, and $[z]_+$ equals to $\max(z, 0)$. In our experiments, we set $\alpha$ to 0.5.

Finally, the total loss is computed as:

$$L_{all} = L_{id} + L_{triplet}$$
3.3. Pooling Method

We found that generalized-mean (GeM) pooling [1] performs better in this task, so we replace the global average pooling with GeM at the end of the backbone. GeM is defined as:

\[ f(g) = \left[ f_1(g) \ldots f_k(g) \ldots f_K(g) \right]^T, \]
\[ f_k(g) = \left( \frac{1}{|X_k|} \sum_{x \in X_k} x^p \right)^{1/\alpha_k} \]  

(4)

, we also try to concat the global average pooling and global max pooling, and fast global average pooling [7], but both of them don’t work.

3.4. Multi-Scale Model Training

We train four models with same architecture, each of which has a different input image size to make the whole network learn multi-scale information. The input image size of the four models are \(320 \times 320\), \(384 \times 384\), \(416 \times 416\). For an image from original dataset, we first shrink it to a random size, and then resize the shrinked image to four kinds of sizes mentioned above. In this way, we get four scaled images and we can use them to train the four models respectively. Since the whole network is trained with both blur images and clear images, it can distinguish the blurred image better.

4. Post-Processing

4.1. Vehicle Class/Brand Filter

Generally the similarity of vehicle images is greatly affected by the camera’s shooting position. For some vehicles of different types or brands, the appearance similarity of pictures may still be extremely high. Therefore, we introduce a coarse vehicle classification model and a vehicle main brand prediction model to assist the vehicle Re-ID task. We use the synthetic data provided by the competition to train the vehicle coarse classification model. At the same time, we mark main brands of some vehicles on the training set of real vehicles and use them to train the vehicle brand model. During the test, we predict the vehicle type and brand of the query and gallery images. We increase the similarity of image pairs which have the same type of vehicle brand or vehicle class to improve the accuracy of vehicle Re-ID, this process is shown in Figures 4.

| method               | mAP   | top-1  |
|----------------------|-------|--------|
| ResNeXt-101-IBN      | 0.6147| 0.7024 |
| + Re-ranking         | 0.6584| 0.7551 |
| + Attribute          | 0.6847| 0.7988 |
| + Camera Multex      | 0.6943| 0.8051 |
| + Ensemble           | **0.7263** | **0.8344** |

Table 1. Ablation Study of Post-processing Part in validation data

4.2. Fine-Tune With Vehicle Orientation

It is more difficult to search between the vehicles that face front or back and the vehicles that face side than to
search between the vehicles that face front and the vehicles that face back. Therefore, in order to make the difficulty of vehicle re-identification consistent in all situations, we artificially reduce the difficulty of mutual searching between the front/back facing and the side facing vehicles.

We use the provided synthetic data to train the vehicle orientation prediction model. We divide 0–360 degrees into 36 equal parts to get a label of orientation, and train a 36-category classification model. We use the trained model to predict the direction of the vehicle in the test set, and use a unit vector whose direction is consistent with the vehicle orientation to represent the feature of orientation, this process is shown in Figures 5.

Since it is easy to search between front facing vehicles and back facing vehicles, we fold the vehicle orientations result horizontally, as shown in the Figures 6, so that the feature similarity between front/back facing vehicle and side facing vehicle will be less than it between front facing and back facing vehicles. In practice, we subtract the similarity matrix of orientation from the similarity matrix of re-id with a certain weight $\lambda$.

### 4.3. Camera Mutual Exclusion

In order to make full use of the extra information in the test set, we utilize the camera information and propose the camera mutual exclusion strategy. It can be summarized into two aspects. From the perspective of query-to-gallery, when an image $A$ retrieves the first image from camera $\tau$, following the retrieval order, the remaining images which from camera $\tau$ will be artificially moved out retrieval results. From the perspective of gallery-to-query, we find that the vehicles with the same identify in the query all come from different cameras. So when one gallery image $I_g$ is the nearest neighbor of multiple query images that are from the same camera, we take only the closest query image as the $I_g$’s positive sample, and the other query images will be moved out retrieval results.

### 5. Experiments

#### 5.1. Implementation Details

We adopt IBN-ResNet-101, IBN-ResNeXt-101, IBN-SE-ResNet101 as the backbone networks. Given the features extracted by the backbone network, most of Re-ID networks use global average pooling (GAP) to obtain a feature vector.

Following a strong Re-ID baseline [15], we add an BNNeck layer after the backbone. In the inference stage, we choose the feature after the BNNeck layer for person id prediction. In the training stage, the feature before BNNeck layer is used to compute triplet loss and the feature after BNNeck layers is used to compute CosFace loss, this process is shown in Figure 2. We train our model with SGD optimizer, setting the momentum to 0.9. The initial learn-
Figure 7. Visualization of the final retrieval results. The first column shows the query images captured by different cameras, and each row shows the top 5 gallery images retrieved from left to right according to the similarity score. The images in green boxes are true positives, while the images in red boxes are false positives.

The learning rate is set to 0.002 and we adopt the cosine strategy to decay the learning rate.

5.2. Performance Evaluation of Challenge Contest

We report our challenge contest performance of the track2: City-Scale Multi-Camera Vehicle Re-identification. In track2, we won 5th place among all the teams with the mAP of 0.6373, as shown in the Table 3. The actual retrieval results of some queries in the contest are shown in Figure 7. The ablation study of post-processing is shown in Table 1 and Table 2. The ablation study shows that the vehicle re-identification combined with attribute (brand/type/orientation), re-ranking and models ensemble have a great improvement in model performance. In contrast, the camera mutual exclusion strategy improves the model performance slightly.

6. Conclusion

In this paper, we propose several effective methods to achieve remarkable results in the CVPR 2021 AI City Challenge. We utilize the orientation and brand information of vehicles to improve the performance of vehicle ReID. We introduce a multi-scale model training method to make the model adapt to both blurred and clear images. Since the background areas of some images are quite large, we introduce vehicle detection to cut the vehicle part from original images in the dataset. We utilize mutual exclusion between cameras to optimize the final retrieval results. Finally, our proposed system rank number 5 (team ID 125) among all the teams with the mAP of 0.6373 for City-Scale Multi-Camera Vehicle Re-identification.

References

[1] Maxim Berman, Hervé Jégou, Andrea Vedaldi, Iasonas Kokkinos, and Matthijs Douze. Multigrain: a unified image embedding for classes and instances, 2019.

[2] Ruihang Chu, Yifan Sun, Yadong Li, Zheng Liu, Chi Zhang, and Yichen Wei. Vehicle re-identification with viewpoint-aware metric learning. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 8282–8291, 2019.

[3] Stéphane d’Ascoli, Hugo Touvron, Matthew Leavitt, Ari Morcos, Giulio Biroli, and Levent Sagun. Convit: Improving vision transformers with soft convolutional inductive biases, 2021.

[4] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. An image is
worth 16x16 words: Transformers for image recognition at scale, 2020. 2

[5] Bing He, Jia Li, Yifan Zhao, and Yonghong Tian. Part-regularized near-duplicate vehicle re-identification. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 3997–4005, 2019. 2

[6] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition, 2015. 2

[7] Lingxiao He, Xingyu Liao, Wu Liu, Xincheng Liu, Peng Cheng, and Tao Mei. Fastreid: A pytorch toolbox for general instance re-identification. arXiv preprint arXiv:2006.02631, 6(7):8, 2020. 4

[8] Shuting He, Hao Luo, Pichao Wang, Fan Wang, Hao Li, and Wei Jiang. Transreid: Transformer-based object re-identification, 2021. 3

[9] Jie Hu, Li Shen, Samuel Albanie, Gang Sun, and Enhua Wu. Squeeze-and-excitation networks, 2019. 2

[10] Pirazh Khorramshahi, Neehar Peri, Jun cheng Chen, and Jie Hu, Li Shen, Samuel Albanie, Gang Sun, and Enhua Wu. Shuting He, Hao Luo, Pichao Wang, Fan Wang, Hao Li, and Yonghong Tian. Part-regularized near-duplicate vehicle re-identification. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 3997–4005, 2019. 2

[11] Shuang Li, Slawomir Bak, Peter Carr, and Xiaogang Wang. Diversity regularized spatiotemporal attention for video-based person re-identification, 2018. 1

[12] Yawei Li, Kai Zhang, Jiezhang Cao, Radu Timofte, and Luc Van Gool. Localvit: Bringing locality to vision transformers, 2021. 2

[13] Hongye Liu, Yonghong Tian, Yaowei Yang, Lu Pang, and Tiejun Huang. Deep relative distance learning: Tell the difference between similar vehicles. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2167–2175, 2016. 2

[14] Xiaobin Liu, Shiliang Zhang, Qiongmin Huang, and Wen Gao. Ram: a region-aware deep model for vehicle re-identification. In 2018 IEEE International Conference on Multimedia and Expo (ICME), pages 1–6. IEEE, 2018. 2

[15] Hao Luo, Youzhi Gu, Xingyu Liao, Shengqi Lai, and Wei Jiang. Bag of tricks and a strong baseline for deep person re-identification, 2019. 5

[16] Xingang Pan, Ping Luo, Jianping Shi, and Xiaoou Tang. Two at once: Enhancing learning and generalization capacities via ibn-net, 2020. 2

[17] Florian Schroff, Dmitry Kalenichenko, and James Philbin. Facenet: A unified embedding for face recognition and clustering. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 815–823, 2015. 2

[18] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition, 2015. 1

[19] Yifan Sun, Changmao Cheng, Yuhan Zhang, Chi Zhang, Liang Zheng, Zhongdao Wang, and Yichen Wei. Circle loss: A unified perspective of pair similarity optimization. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 6398–6407, 2020. 2

[20] Yifan Sun, Liang Zheng, Yi Yang, Qi Tian, and Shengjin Wang. Beyond part models: Person retrieval with refined part pooling (and a strong convolutional baseline). In Proceedings of the European conference on computer vision (ECCV), pages 480–496, 2018. 2

[21] Zheng Tang, Milind Naphade, Ming-Yu Liu, Xiaodong Yang, Stan Birchfield, Shuo Wang, Ratnesh Kumar, David Anastasiu, and Jenq-Neng Hwang. Cityflow: A city-scale benchmark for multi-target multi-camera vehicle tracking and re-identification. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 8797–8806, 2019. 3

[22] Hongbo Wang, Jiaying Hou, and Na Chen. A survey of vehicle re-identification based on deep learning. IEEE Access, 7:172443–172469, 2019. 1

[23] Huibing Wang, Jinjia Peng, Dongyan Chen, Guangqi Jiang, Tongtong Zhao, and Xianping Fu. Attribute-guided feature learning network for vehicle reidentification. IEEE MultiMedia, 27(4):112–121, 2020. 2

[24] Hao Wang, Yitong Wang, Zheng Zhou, Xing Ji, Dihong Gong, Jingchao Zhou, Zhifeng Li, and Wei Liu. Cosface: Large margin cosine loss for deep face recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 5265–5274, 2018. 2

[25] Zhongdao Wang, Luming Tang, Xihui Liu, Zhuliang Yao, Shuai Yi, Jing Shao, Junjie Yan, Shengjin Wang, Hongsheng Li, and Xiaogang Wang. Orientation invariant feature embedding and spatial temporal regularization for vehicle re-identification. In Proceedings of the IEEE International Conference on Computer Vision, pages 379–387, 2017. 2

[26] Saining Xie, Ross Girshick, Piotr Dollár, Zhuowen Tu, and Kaiming He. Aggregated residual transformations for deep neural networks, 2017. 1

[27] Gang Zhang, Chongruo Wu, Zhongyue Zhang, Yi Zhu, Zhi Zhang, Haibin Lin, Yue Sun, Tong He, Jonas Muller, R. Mannmatha, Mu Li, and Alexander Smola. Resnest: Split-attention networks. arXiv preprint arXiv:2004.08955, 2020. 2

[28] Xuanmeng Zhang, Minyue Jiang, Zhedong Zheng, Xiao Tan, Errui Ding, and Yi Yang. Understanding image retrieval re-ranking: A graph neural network perspective, 2020. 1

[29] Xuan Zhang, Hao Luo, Xing Fan, Weilai Xiang, Yixiao Sun, Qiqi Xiao, Wei Jiang, Chi Zhang, and Jian Sun. Align-dreid: Surpassing human-level performance in person re-identification. arXiv preprint arXiv:1711.08184, 2017. 2

[30] Zhun Zhong, Liang Zheng, Donglin Cao, and Shaozi Li. Re-reid: Surpassing human-level performance in person re-identification. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 6398–6407, 2019. 2

[31] Zhi Zou, Xiaodong Yang, Zhiding Yu, B. V. K. Vijaya Kumar, and Jan Kautz. Joint disentangling and adaptation for cross-domain person re-identification, 2020. 1