Vehicle Re-identification with Location and Time Stamps

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Abstract

This paper focuses on the problem of vehicle re-identification (Re-ID). In our attempt, we propose a re-identification framework by exploiting vehicle location and time stamps. The location and time information have the potential to cover the shortage of appearance-based feature representations. First, we introduce an ensemble technique to combine the informative cues of multiple Re-ID models effectively. To further improve the accuracy, we then build up a system to acquire the vehicle location and time stamps. Specifically, we utilize the detected results to obtain the needed information. With the help of the proposed system, we can remove irrelevant images from a given ranking list. Our system finished 3rd place in the 2019 AI-City challenge for city-scale multi-camera vehicle re-identification.

Figure 1: Images of different cameras. These images come from the same moment in the same scene, and the camera angle is changed.

1. Introduction

Vehicle re-identification (Re-ID) [13, 14, 22] aims to match a specific vehicle captured from multiple cameras. The vehicle Re-ID plays a crucial role and has attracted more interest in the computer vision community.

Identifying vehicles in different scenes and angles remains challenging, and the reasons mainly exist in two aspects. First, in traffic scenarios, vehicle feature extraction is susceptible to illumination, camera viewpoints and occlusion. For example, the color of the images in the backlit camera will change, which is a severe problem for the human eye as well as the computer. Meanwhile, for feature extraction, it is difficult to handle vehicle images at different angles (front and rear). Second, it is difficult to achieve accurate re-identification results by only using image information. Typically, most large vehicle datasets contain a large number of vehicles of the same model and similar colors. In this case, vehicles of different identities are very likely to affect the results of the identification. To alleviate the impact of excessive data, a natural way is to use location and time stamps to reduce the number of vehicles in the gallery database.

Our system is based on the feature representations of vehicles. In this paper, we choose a CNN-based network as the feature extractor [22, 23]. To enhance the discriminative ability of representations, we introduce an effective ensemble technique. It concatenates informative cues of different Re-ID feature extractors. The proposed method is most effective when extractors are complementary. To this end, we train several extractors under different conditions (*e.g.,* different data augmentation tactics and loss functions).

Appearance-based representations have some limitations, *i.e.,* distinguishing vehicles with similar colors and identifying vehicles with different poses. For example, appearance-based representations might have difficulty in

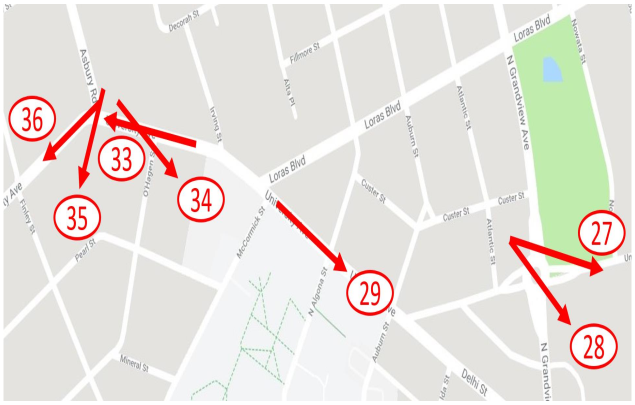


Figure 2: Some urban environment and camera distribution of the vehicle re-identification task. The red arrows denote the locations and directions of cameras. In this dataset, the original videos and calibration details are available. Thus, for each test image, there exists a location stamp and a time stamp.

identifying red vehicles with different poses in Fig. 1. To alleviate this problem, we propose to utilize location and time information to improve retrieval accuracy. To obtain the vehicle location and time stamps, we first use Mask-RCNN [9] to generate the detection bounding box. Then, we calculate the feature distances between the detected bounding boxes and test images. Thus, we can obtain the location and time details of test vehicles by associate camera information. Depending on the stamps of vehicles, we set several thresholds to control the number of gallery vehicles for each query. By setting the latest arrival time and earliest departure time, we can get an appropriately sized gallery set.

In summary, we make the following contributions.

- We propose an ensemble technique to combine information from complementary Re-ID models effectively.
- We develop a vehicle location and time acquisition system. By taking raw video as input, this system extracts valid location and time details.
- We introduce a stamps method to remove incorrect images by giving query images latest arrival time and earliest departure time.

2. Related Work

Vehicle re-identification is closely related to person re-identification. Many previous methods [8, 32, 6, 26] of re-identification extract the feature using global color and texture histograms. Some other Re-ID techniques [29, 30] model person appearance using local features which are extracted from small sub-regions in images, such as SIFT [16].

With the development of deep learning techniques [20, 10], state-of-the-art person re-identification methods adopted deep learning techniques [19, 1, 27, 31, 33]. Ahmed *et al.* [1] designed a pairwise verification CNN model for person re-identification with a pair of cropped pedestrian images as input and employed a binary verification loss function for training. Xiao *et al.* [27] mix several Re-ID datasets together and train a Convolutional Neural Network (CNN) to recognize person identities. This paper adopts CNN for feature learning under the classification mode, which is shown to produce competitive accuracy without losing efficiency potentials [22].

A few works [3, 26, 4] use target pose priors (pose cues) for person re-identification very recently. S.Bak *et al.* [3] propose to learn a generic metric pool which consists of metrics. Z. Wu *et al.* [26] build a model for human appearance as a function of poses, using training data gathered from a calibrated camera and then apply this "pose prior" in online re-identification to make matching and identification more robust. Cho *et al.* [4] propose a novel framework for person re-identification by analyzing camera viewpoints and person poses, which robustly estimates target poses and efficiently conducts multi-shot matching based on the target pose information.

As several vehicle datasets [15, 14, 13] are proposed, vehicle re-identification has attracted more attention in the past several years. Liu *et al.* [13] propose a deep relative distance learning method to learn the difference between vehicles and release a new VehicleID dataset which contains two viewpoints. Then, VeRi-776 dataset is proposed [15, 14] with more available points. They utilize vehicle appearance together with plates and spatial-temporal information to solve the vehicle re-identification problem. A two-stage framework is proposed by Shen *et al.* [17]. This method incorporates complex spatio-temporal information for effectively regularizing the vehicle re-identification results. Wang *et al.* [24] propose an orientation invariant feature embedding module and a spatial-temporal regularization module.

3. Proposed System

The proposed vehicle Re-ID system aims to identify vehicles in multiple videos captured at different locations or different times. As shown in Fig. 3, the Re-ID system mainly consists of three parts: Vehicle Feature Extractor, Stamps Acquisition, and Spatial-Temporal Constraint. The first part is named the feature extractor. In this part, we introduce the way to extract feature representations by the feature ensemble method. Then, in the second part, we propose to get vehicle location and time stamps by using detected

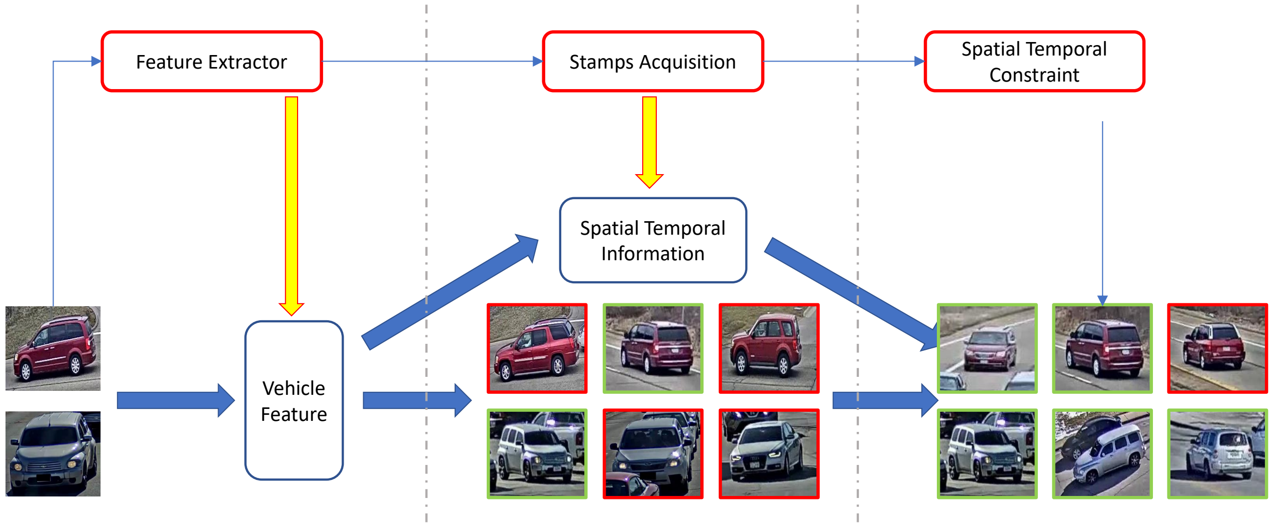


Figure 3: Overall proposed vehicle Re-ID framework. The Re-ID system contains three parts. Given the query image, vehicle appearance feature is extracted by feature extractor mentioned. Next, several gallery images are selected by the distance of feature with the query image. Meanwhile, the spatial-temporal information of the query image and selected images could be acquired by stamps acquisition. At final, impossible gallery images are filtered out based on the spatial-temporal constraint of the query image and re-rank the given rank list.

results. Finally, we perform vehicle Re-ID by limiting the number of gallery images.

3.1. Vehicle Feature Extractor

In the vehicle Re-ID task, it is crucial to gain robust feature representations. In this paper, we construct image-based feature extractor using deep convolution network. We choose DenseNet121 [12] architecture as the backbone of our feature extractor. We train the feature extractor using triplet loss and cross-entropy loss. The triplet loss is defined as:

$$L_{Tri} = [d_p - d_n + \alpha]_+, \tag{1}$$

where d_p and d_n are the distances of positive pair and negative pair in the feature space. The α is the margin of triplet loss, and $[z]_+$ equals to $max(z, 0)$. We set α 0.3 in the experiment.

To prevent the feature extractor from over-fitting during training, we utilize label smoothing regularization (LSR) [21]. Given an image, we denote y as truth ID label, p_i as ID prediction logits of class i, and N as the total number of vehicle identities. The cross entropy loss is computed as:

$$L_{cross} = \sum_{i=1}^{N} -q_i \log(p_i) \begin{cases} q_i = 0, y \neq i \\ q_i = 1, y = i. \end{cases} \tag{2}$$

LSR modifies the q_i to:

$$q_i = \begin{cases} 1 - \frac{N-1}{N}\varepsilon & \text{if } i = y \\ \varepsilon/N & \text{otherwise,} \end{cases} \tag{3}$$

where ε is a small constant to encourage the model to be less confident on the training set. We set ε 0.1 in this paper.

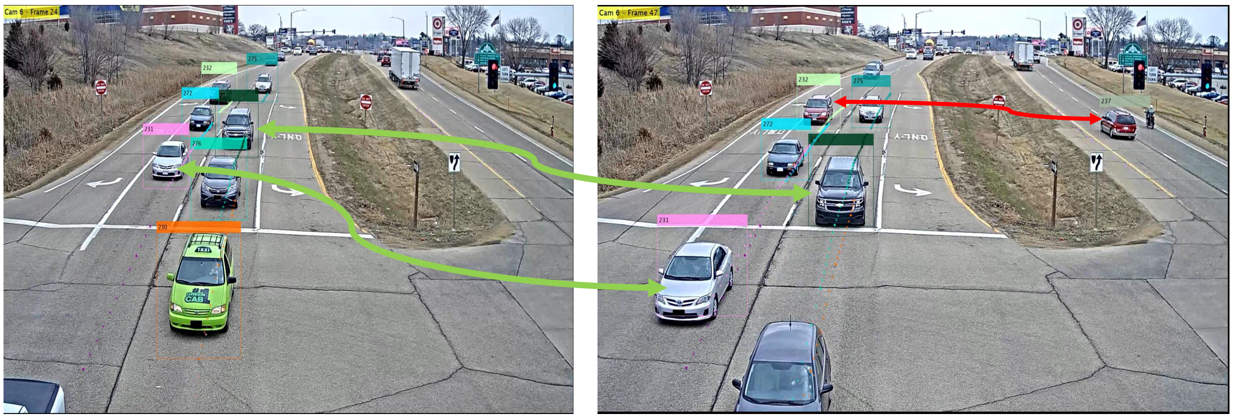
Thus,the overall objective of feature extractor is:

$$L = L_{cross} + \alpha L_{Triplet} \tag{4}$$

α is the balanced weight of the triplet loss. In the experiment, α is set to be 1.

Feature ensemble. To make the representations more discriminative, we propose to concatenates informative cues of different Re-ID feature extractors. This practice requires the presentations of different models are complementary. To meet this requirement, we train three networks under different conditions: 1) train feature extractor with LSR and triplet loss (hard margin); 2)train feature extractor with LSR and triplet loss (soft margin); 3)utilize Jitter Augmentation, LSR, and triplet loss (hard margin). Three networks are trained *separately*.

Given three trained networks, we could extract three feature vectors for an image. We firstly normalize each feature vector by L_2 Normalization, and then concatenates them as the final feature representations for an image. Note the feature ensemble is adopted during inference.



Frame 26 frame 47

Figure 4: Visual examples of vehicle re-identification task. One vehicle could not appear at different positions in the same frame of the same camera. Though these images have similar appearance feature. For example, both of the two vehicles linked by red line are red multi-purpose vehicles, but they appear in the same time with multiple locations. Furthermore, most vehicles move in a straight line at a constant speed in the lane, such as two pair of vehicles linked by the green line. We take advantage of these points in the proposed ReID system and improve the performance of vehicle retrieval.

Query expansion. Vehicle re-identification is also an image retrieval problem. Thus, we adopt query expansion [2, 5] to further improve the discriminative ability of feature representations. The basic principle of query expansion lies in that given several vehicles with gradually different perspectives or lighting conditions, and intermediate vehicles can help us to connect them. The query expansion works as follow: given the top k retrieved results of a query image and query itself, we sum-aggregate and re-normalize the feature representations of them. This leads to new feature representations of the query image. The k is set to 10 in this paper.

Temporal pooling for gallery. The gallery consists of several image sequences. To make use of temporal information, we use temporal pooling for gallery images during inference. Specifically, for each image in a sequence, we adopt average pooling for it and its subsequent $T-1$ images (T is set to 5 in this paper):

$$f_c = \frac{1}{T}\sum_{t=1}^{n} f_c^t. \tag{5}$$

3.2. Stamps Acquisition

In this paper, we introduce location and time stamps to assist vehicle re-identification task. In previous vehicle Re-ID works, appearance-based methods focus on exploiting good feature representations that make objects with the same class have a lower distance. However, these features are difficult to distinguish vehicles with similar colors and poses. Therefore, to alleviate these problems, we propose to introduce the location and time details in this paper.

To get vehicle location and time stamps, we introduce the videos in Track 1 (city-scale multi-camera vehicle tracking). As for vehicle re-identification, only test images are provided, and there is no location and time of the images. Meanwhile, the raw videos in Track 1 have location and time details for the vehicles appearing in the videos. Thus, it is reasonable to combine the test images with the videos.

In this work, we use the mentioned extractor to get the needed features. On the one hand, the extractor is utilized to extract the features of test images, including query images and gallery images. On the other hand, we also use the extractor to get the features of the detection patches. We calculate the feature distance between test images and detection patches. Then, each test image will have a ranking list. Finally, we take the first detection patch from the list to get its location stamp as well as the time stamp.

3.3. Spatial-Temporal Constraint

The motivation for introducing spatio-temporal information is that spatio-temporal details can strictly reduce the number of irrelevant gallery images. Unlike humans who are more likely to wander randomly, there are more strict rules for vehicle trajectories. In the real world, the vehicles always follow traffic lanes and the speed remains approximately the same. Therefore, given a scenario, the vehicle moving pattern between cameras should also follow a certain rule.

As mentioned in [25], there are two key findings. First, one vehicle can not appear at multiple locations at the same time. Second, vehicles should move continuously along the time. Based on this nature, we propose to use location and time stamps to remove irrelevant images from a given ranking list. Based on these two findings, vehicles are certainly to move continuously.

In the proposed system, the location and time stamps are leveraged for the gallery refinement. We extract the bounding boxes form AI-City 2019 vehicle tracking dataset (track-1) and compare them to the query/gallery images. The Re-ID features from the ensemble model are used for this assignment task. Once we acquire the query/gallery-detection matching, we add the location and time stamps from the detection to the query/gallery image. For simplicity, the location stamp is set as the camera location.

During training, we construct a transfer time matrix with the maximum transfer time between each pair of camera. For the cameras that not appeared in the training set, we use the distance between camera pairs to estimate the maximum transfer time. Once the transfer time matrix is complete, at testing, we use it to refine the gallery by ruling out the impossible images (transfer time longer than the corresponding value in the maximum transfer time matrix).

4. Experiment

4.1. Datasets

Datasets. There are mainly four existing vehicle datasets related to vehicle re-identification, including VeRi-776 [15, 14], VehicleID [13], BoxCars21k [18], and CompCars [28]. VeRi-776 [15, 14] is a benchmark dataset for vehicle re-identification that is collected from real-world scenarios, with over 50,000 images of 776 vehicles in total. In this paper, we first validate the feature ensemble method on VeRi-776 and then report the result of the whole system on CityFlow [22].

Evaluation protocol. We adopt the Cumulative Matching Characteristic (CMC) curve for Re-ID evaluation. Besides, since multiple true positives should be returned for each query bounding box, We also adopt the mean average precision (mAP) for Re-ID evaluation. The performance on CityFlow is reported by an online evaluation system [1].

4.2. Implementation Details

To learn feature extractor, we adopt IDE+ [31, 33] as the feature learning method. All the images are resized to 256×256. During training, we adopt random flipping and random cropping as data augmentation methods. Dropout probability is set to 0.5. We adopt Densenet121 [12] as the backbone network. We use mini-batch SGD to train CNN models on a V100 GPU in a total of 100 epochs. The initial learning rate is set to 0.01 for the layer in the backbone network, and to 0.02 for the remaining layer. Besides, we adopt the Warmup Learning strategy [7], and spent 10 epochs linearly increasing the learning rate from 10^{-4} to 10^{-2}. The learning rate is decayed to 3.5×10^{-3} and 10^{-4} at 30th epoch and 60th epoch, respectively. We modify the last stride of Densenet121 as 1. This leads to higher spatial size, which is beneficial for feature learning.

For the triplet loss, we use batch-hard sampling method as in [11]. Moreover, we sample 4 classes and 16 images for each class in a mini-batch. During testing, given an input image, we extract the 1,024-dim Pool5 vector for retrieval under the Euclidean distance.

[1]https://www.aicitychallenge.org/2019-evaluation-system/

Table 1: Comparison of different components on the VeRi-776 dataset.

Methods	mAP	CMC-1	CMC-5	CMC-10
model1	69.1	92.1	97.0	98.4
model2	68.7	91.6	96.5	98.0
model3	68.9	91.9	97.0	98.1
model ensemble	70.5	93.0	97.9	99.0
+ query expansion	**70.8**	**93.2**	**98.0**	**98.9**

Table 2: Leader board on AI-City challenge for city-scale multi-Camera vehicle re-identification.

Ranking	Team ID	mAP Score
1	59	0.8554
2	21	0.7917
3	**97 (ours)**	**0.7589**
4	4	0.7560
5	12	0.7302
6	53	0.6793
7	131	0.6091
8	5	0.6078
9	78	0.5862
10	127	0.5827

4.3. Experimental results

VeRi-776. To validate the effectiveness of feature ensemble method, we conduct experiment on VeRi-776 and report results in Table 1. As shown in Table 1, the three feature extractors (model1, model2, and model3) achieve almost the same CMC results. With the help of feature ensemble, the final feature obtains 93.0 % in CMC-1 accuracy. Moreover, query expansion further gains 0.2% and 0.3% improvements over feature ensemble in CMC-1 accuracy and mAP, respectively.

CityFlow. In the end, we report the accuracy of the whole system on CityFlow, as shown in Table. 2, our sys-

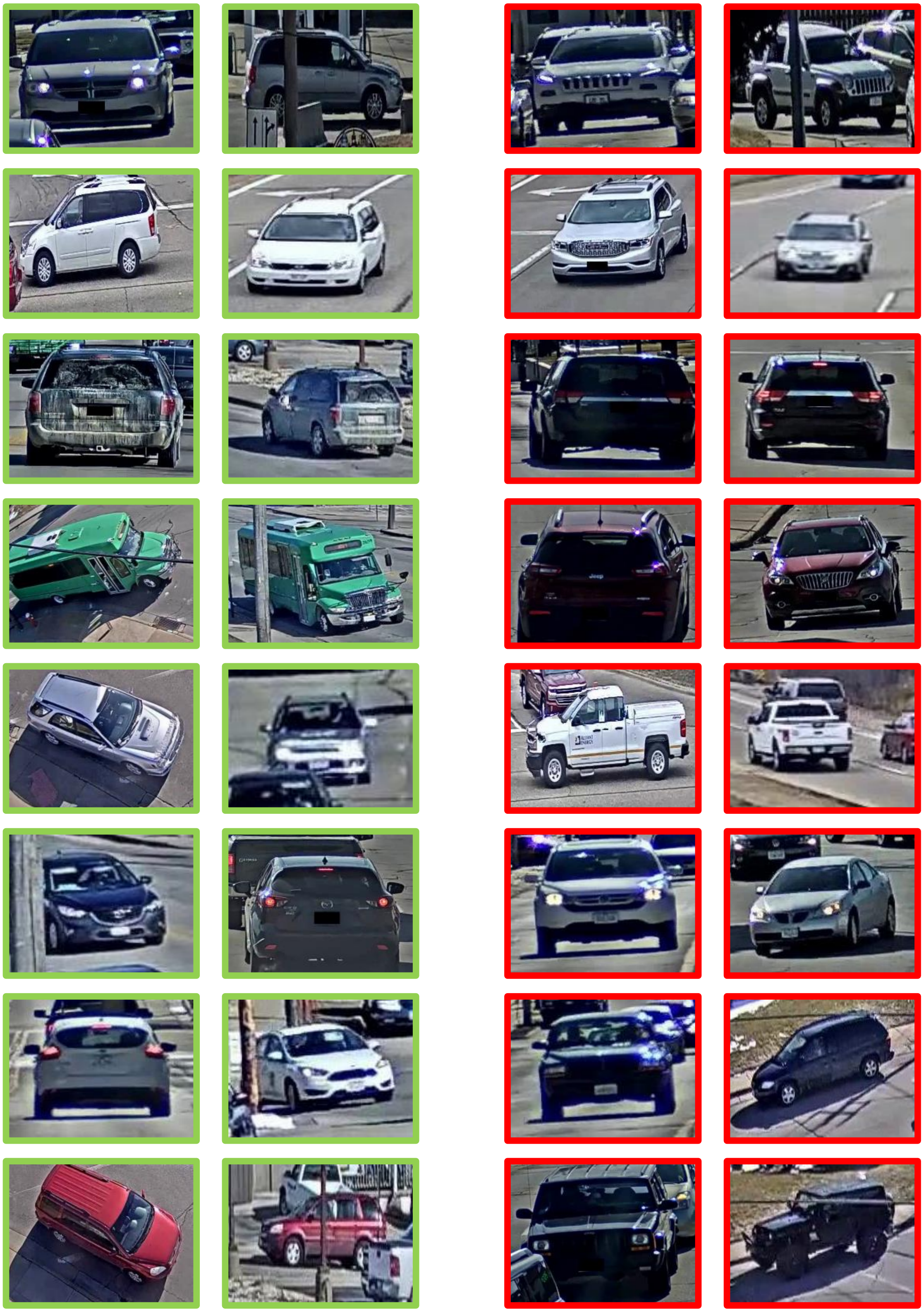


Figure 5: Visual examples of vehicle re-identification results. We show two columns of ranking result. The left column represents the eight pairs of correct samples, and the right column shows another eight pairs of vehicles with mistaken re-identified, thought both of vehicle in each pair have the similar appearance and meet the spatial-temporal constraint.

tem achieves 0.7589 in the mAP score and 0.8916 in CMC-1 score, which yields the third place in the 2019 NVIDIA AI City Challenge Track 2. In Fig. 5, we show some ranking list produced by our system.

5. Conclusion

In this paper, we propose a location and time stamps based vehicle Re-ID system. We utilize vehicle location and time stamps to reduce the number of irrelevant gallery images strictly. We verify the effectiveness of the vehicle feature ensemble on the VeRi-776 dataset. Then, we adopt the feature ensemble in our vehicle Re-ID system to extract feature representations. Finally, the proposed system finished 3^{rd} place in the 2019 AI-City challenge for city-scale multi-camera vehicle re-identification.

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