SJDL-Vehicle: Semi-supervised Joint Defogging Learning for Foggy Vehicle Re-identification

Group Member: Kyle Collins, Tianfie Xu, Michael Tate, Ping Zhang

Presentation Slides Author: Ping Zhang

Date: 04/16/2023

01

Motivation for the work

Address the problem of vehicle re-identification (ReID) in foggy weather condition

important for building intelligent transportation and public security systems.

Foggy weather conditions can significantly degrade the visibility of images, and existing defogging methods are not specifically designed for ReID

- making it difficult for existing ReID methods to accurately identify vehicles.
- not always guarantee improved ReID performance.

Heavy computational burden of most defogging methods

Integrating defogging and ReID models can also increase the complexity of the system due to the heavy computational burden of most

Figure1：Defogged results based on different optimization schemes.

02

Proposed solution

Semi-supervised joint defogging learning (SJDL) system

Represent an improvement: conduct defogging and vehicle re-identification (ReID) simultaneously to alleviate the vehicle ReID problem in foggy weather.

- **consists of two branches: the re-identification branch and the defogging branch**
  - ➢ share a feature extraction module called the collective feature sharing module (CFSM) to
  - ➢ ensure that the fog-free features generated by this module can be used for ReID to cope with the poor visibility problem.

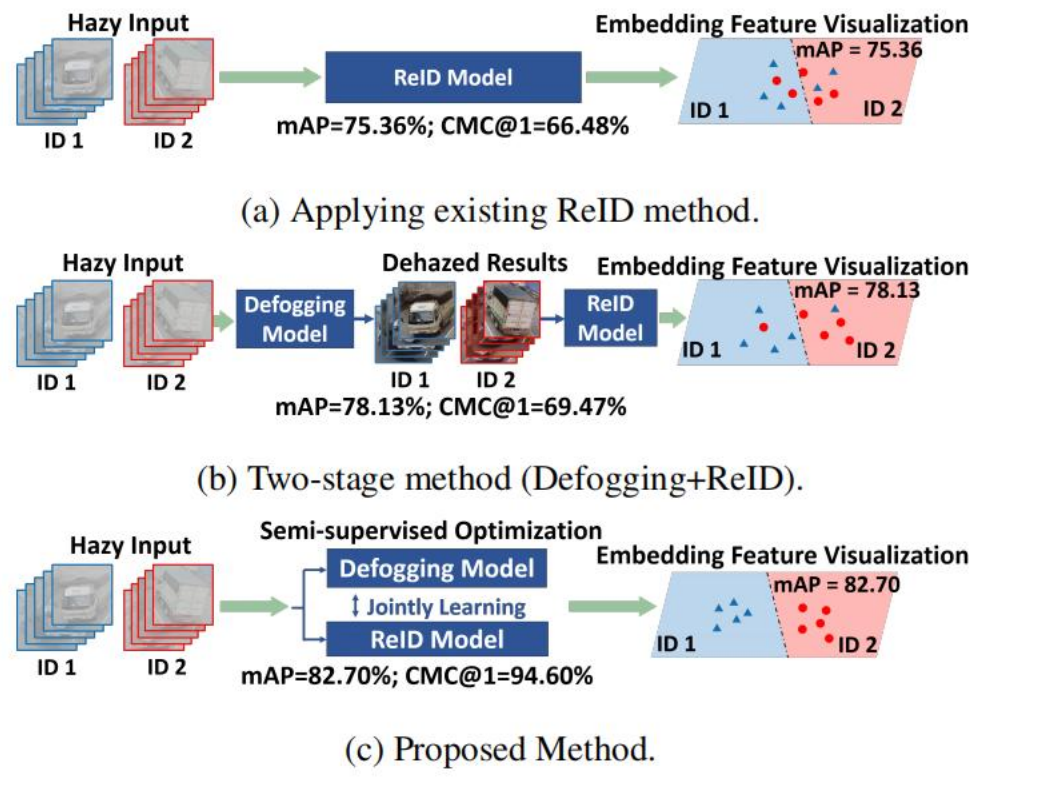


Figure 2: Comparison of different strategies for vehicle ReID in the foggy weather in terms of the mean average pre_x0002_cision (mAP) and CMC@1

02

Proposed solution

Represent an improvement: the proposed system is trained on **both synthetic and real-world data alternatively** to **address the domain gap problem.**

- **Unsupervised and supervised defogging optimizations**, which are based on different sources of input data, are applied for the defogging branch.

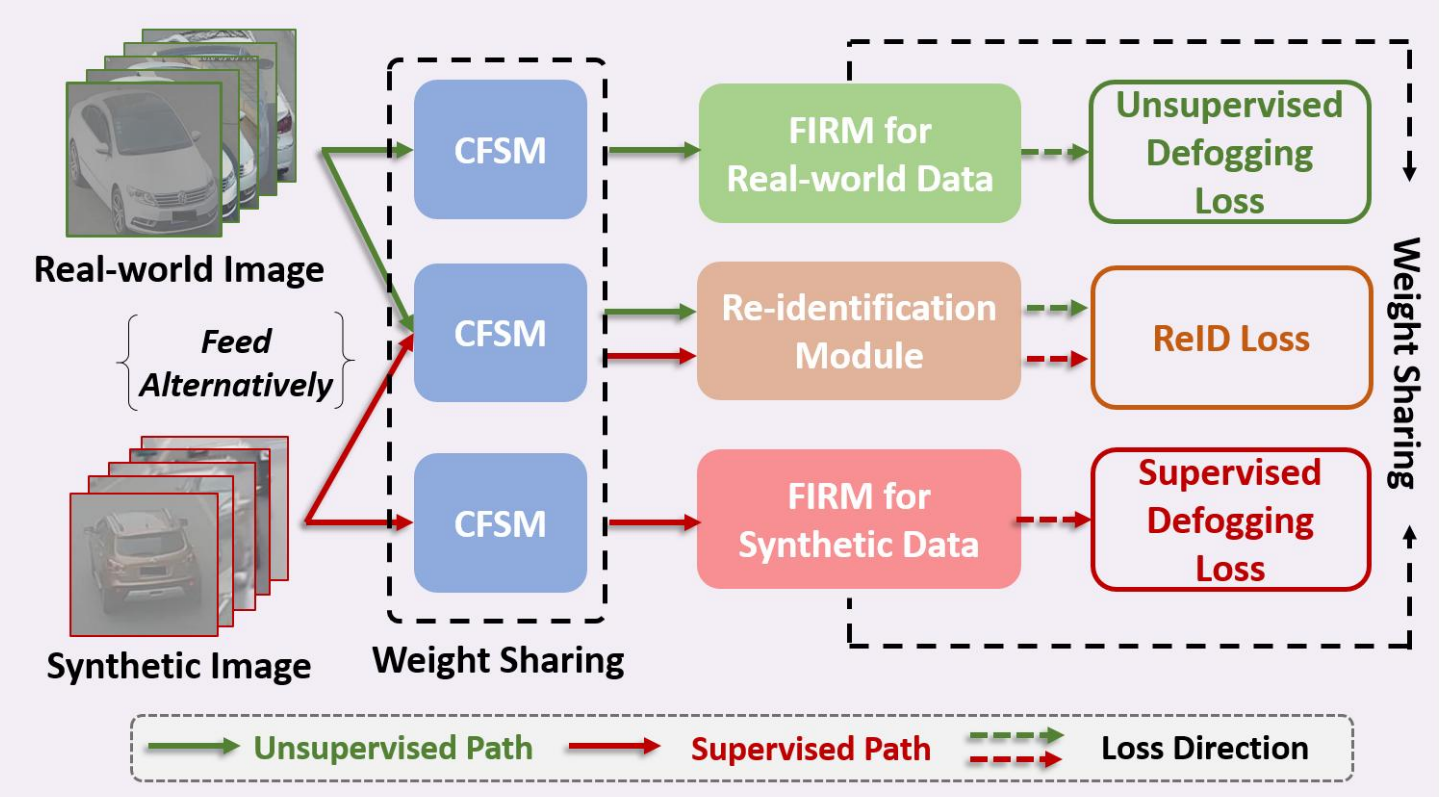


Figure 3: Different sources of data are fed alternatively at the training stage

Proposed solution

Represent an improvement: By this architecture, the performance can be improved significantly without additional computational burden at the inference stage.

- **Training stage**, both branches share a feature extraction module CFSM).
- **Inference stage**, only the CFSM and the ReIDM are required to perform ReID.

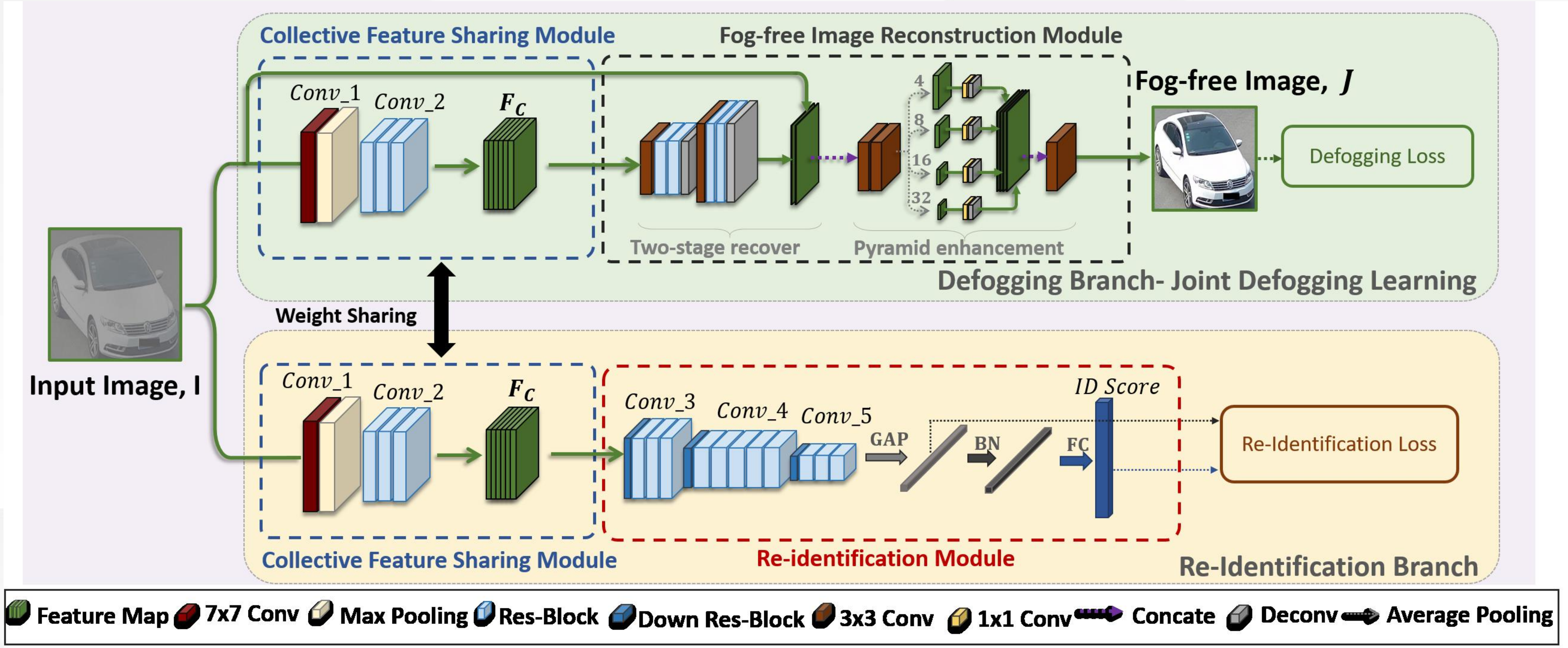


Figure 3: The architecture of the proposed joint defogging learning network for vehicle ReID

03

Experiments - construct the dataset

Figure 4: Examples of the images in FVRID_Real andFVRID_Syn datasets

Set	Train	Probe	Gallery
VERI-Wild	1167/19532	389/389	389/6125
Vehicle-1M	1833/23026	611/611	611/7093
FVRID_Syn	3000/42558	1000/1000	1000/13218

Table 2: The detailed constitution of the FVRID_Syn dataset. (IDs/Images)

Set	Train	Probe	Gallery
VERI-Wild	156/2472	389/389	389/5985
Vehicle-1M	247/2579	611/611	611/6242
FVRID_Real	403/5051	1000/1000	1000/12227

Table 1: The detailed constitution of the FVRID_Real dataset. (IDs/Images)

04

Evaluation - Comparison with the Existing Methods

Method	mAP		CMC@1		CMC@5		CMC@10	
	S	R	S	R	S	R	S	R
Triplet	35.70	36.10	65.10	60.30	82.00	79.20	87.80	85.10
Triplet-defog	51.20	39.00	76.80	62.10	90.60	80.80	94.00	86.30
Triplet-fog	69.10	52.80	87.80	72.50	95.60	89.40	97.80	94.20
VRCF	25.90	36.60	61.70	63.70	76.50	78.80	81.30	83.20
VRCF-defog	61.50	50.80	85.40	78.00	95.10	92.00	97.20	95.40
VRCF-fog	69.00	58.00	88.60	81.10	<u>97.60</u>	93.80	98.40	96.80
VOC	59.70	57.40	86.10	82.80	94.30	94.00	95.60	96.60
VOC-defog	63.40	49.20	87.00	74.10	94.80	89.90	96.50	94.30
VOC-fog	67.10	59.90	88.70	83.50	95.10	94.00	96.50	97.20
VEHICLEX	63.64	61.56	86.50	83.20	95.00	95.20	97.40	97.90
VEHICLEX-defog	73.06	64.82	89.70	83.90	96.70	95.10	98.20	97.60
VEHICLEX-fog	77.86	69.01	91.20	84.80	97.10	96.10	<u>98.70</u>	98.10
DMT	73.90	71.70	93.40	93.20	97.20	97.40	97.90	98.50
DMT-defog	75.10	71.60	93.40	92.40	96.90	97.50	98.30	98.40
DMT-fog	77.30	73.40	<u>94.00</u>	<u>93.40</u>	<u>97.60</u>	<u>97.60</u>	98.60	<u>98.80</u>
PVEN	72.83	75.36	63.73	66.48	84.39	86.53	89.65	91.20
PVEN-defog	81.70	78.13	73.29	69.47	92.50	89.16	96.04	93.43
PVEN-fog	<u>84.55</u>	<u>81.92</u>	76.60	74.09	95.02	92.15	97.84	95.66
TransReID	62.90	64.00	82.40	77.70	92.30	88.80	98.40	94.00
TransReID-defog	66.80	65.30	83.00	76.60	94.10	89.90	98.10	94.60
TransReID-fog	73.90	72.10	84.80	82.60	95.20	90.70	98.70	95.60
Ours	**85.36**	**82.70**	**94.60**	**94.60**	**97.90**	**98.10**	**98.90**	**99.20**

Anootation:
S: FVRID_Syn dataset;
R: FVRID_Real dataset

Table 1: Quantitative evaluation on the foggy ReID datasets.

04

Evaluation - Effectiveness of joint defogging learning and semi-supervised defogging optimization.

- **Baseline： presents the ResNet-50.**
- **JDL：denotes the joint defogging learning only with supervised defogging optimization.**
- **SJDL：presents the JDL mech_x0002_anism with the semi-supervised defogging optimization.**

Module	mAP			CMC@1			CMC@5			CMC@10		
	S	R	Δ	S	R	Δ	S	R	Δ	S	R	Δ
Baseline	81.88	76.17	5.71	94.40	93.40	1.0	97.60	97.50	0.5	98.70	98.50	0.2
JDL	83.04	79.47	3.57	94.50	93.80	0.7	**98.10**	97.90	0.2	98.80	99.00	-0.2
SJDL w/o $\mathcal{L}_{SC}$	84.39	81.50	2.89	94.50	94.20	0.3	98.00	98.00	0.0	98.80	99.00	-0.2
SJDL	**85.36**	**82.70**	**2.66**	**94.60**	**94.60**	**0.0**	97.90	**98.10**	**-0.2**	**98.90**	**99.20**	**-0.3**

Table 4: Effectiveness of the proposed joint defogging learning and semi-supervised defogging optimization.

Annotation: The symbol ’ Δ’ presents the difference between the results of synthetic data and real-world data **(The smaller value indicates better performance for addressing the domain gap problem).**

Evaluation - Effectiveness of joint defogging learning and semi-supervised defogging optimization.

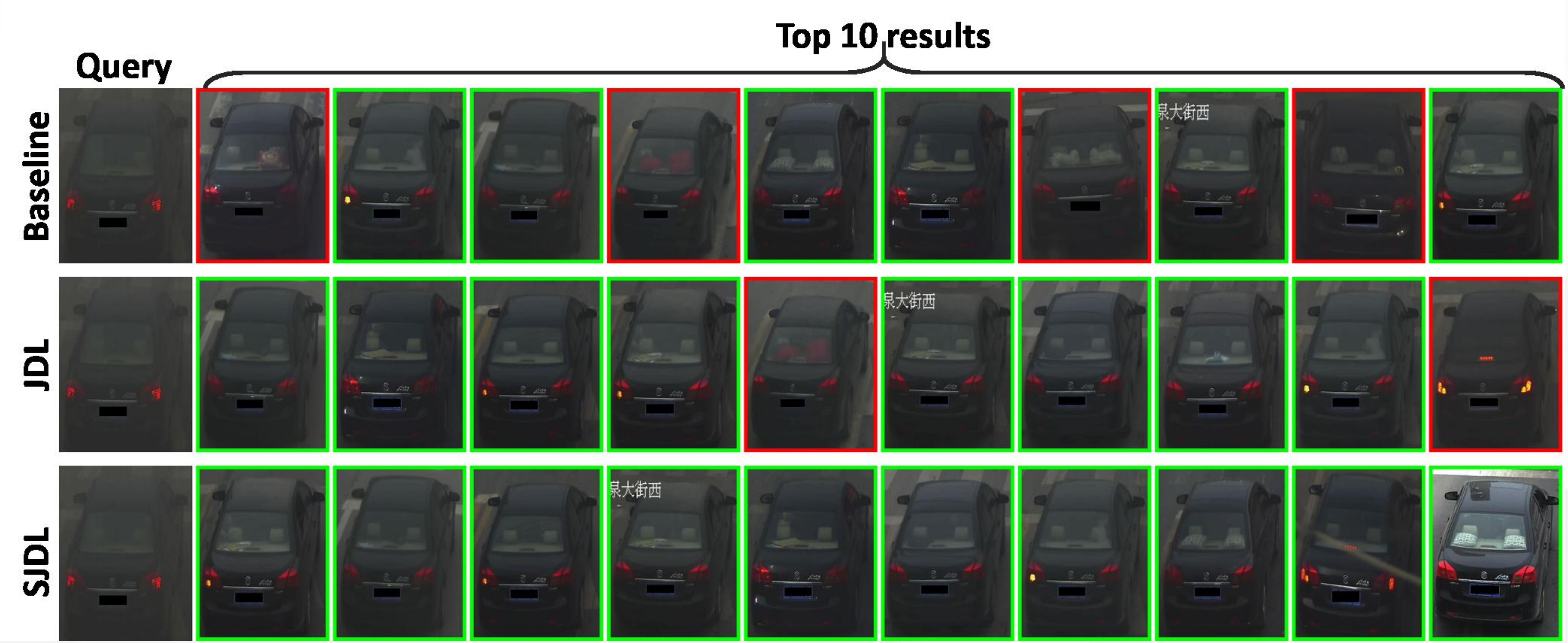


Figure 5: Visualization of the ranking list on FVRID_Real dataset.

05

Contribution of the paper

- A novel training framework that unifies the defogging network and re-identification network is proposed.

- A semi-supervised defogging training mechanism is proposed.

- Construct a dataset called Foggy Vehicle ReID (FVRID).

05 Contribution of the paper- practical implications

- **Whether the proposed solution will work in real-world systems?**

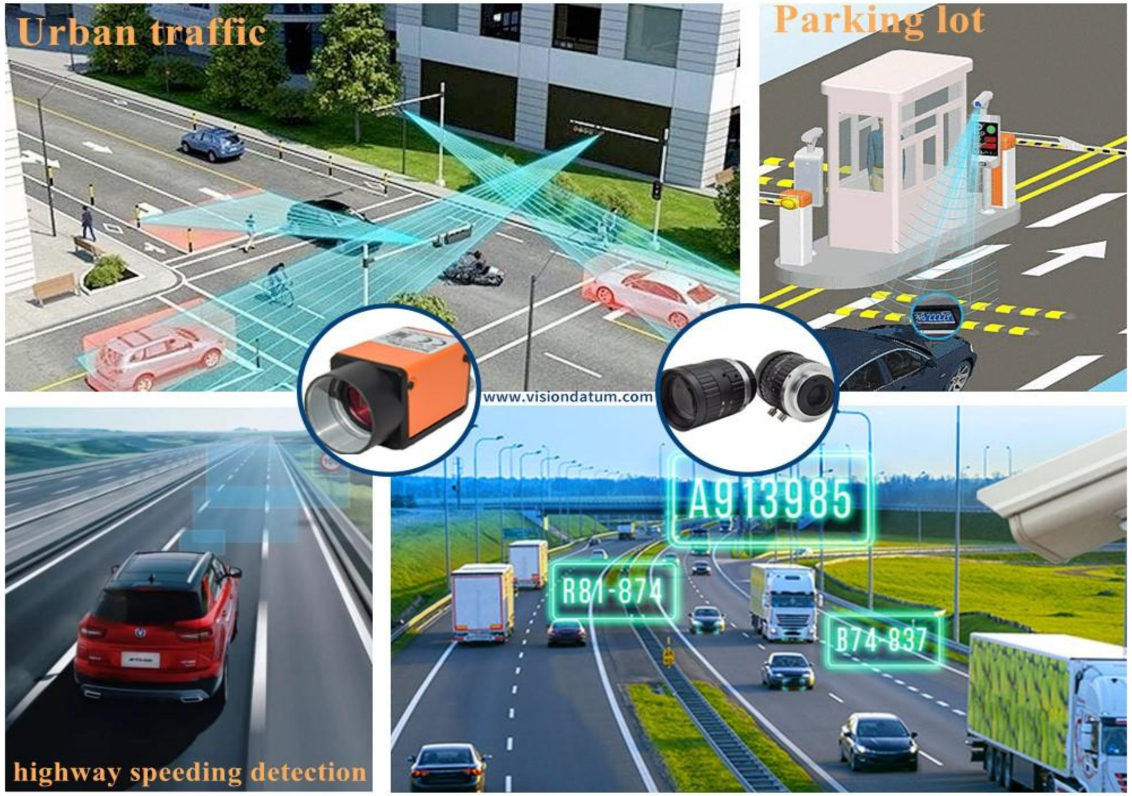
Yes.

Its goal is to find images of the same vehicle in a large gallery set based on a query image under multiple cameras and various viewpoints.

- **Who would want it?**

Intelligent transportation and publisecurity systems.

Vehicle ReID is indispensable for building intelligent transportation and publisecurity systems.



06

Our Questions

- **Does this model can performed well on other dataset in the real world senario?**

It seemed biased towards their model, because they seemed to use the data the model was trained on to evaluate theirs and all the rest, which may have been why their model performed well.

- **Does the Synthetic Dataset construction reasonable?**

They select fog-free images from VERI Wild and Vehicle-1M datasets, Then, they synthesize these images based on the fog synthesis process in. We think, the same fixed algorithm is used to add fog to all the clear image, and the effect is quite different from the real world senario

- **We didn't understand what the cumulative matching characteristics were based on when evaluating the model.**

THANK YOU FOR LISTENING !