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RAM: A Region-Aware Deep Model for Vehicle Re-Identification

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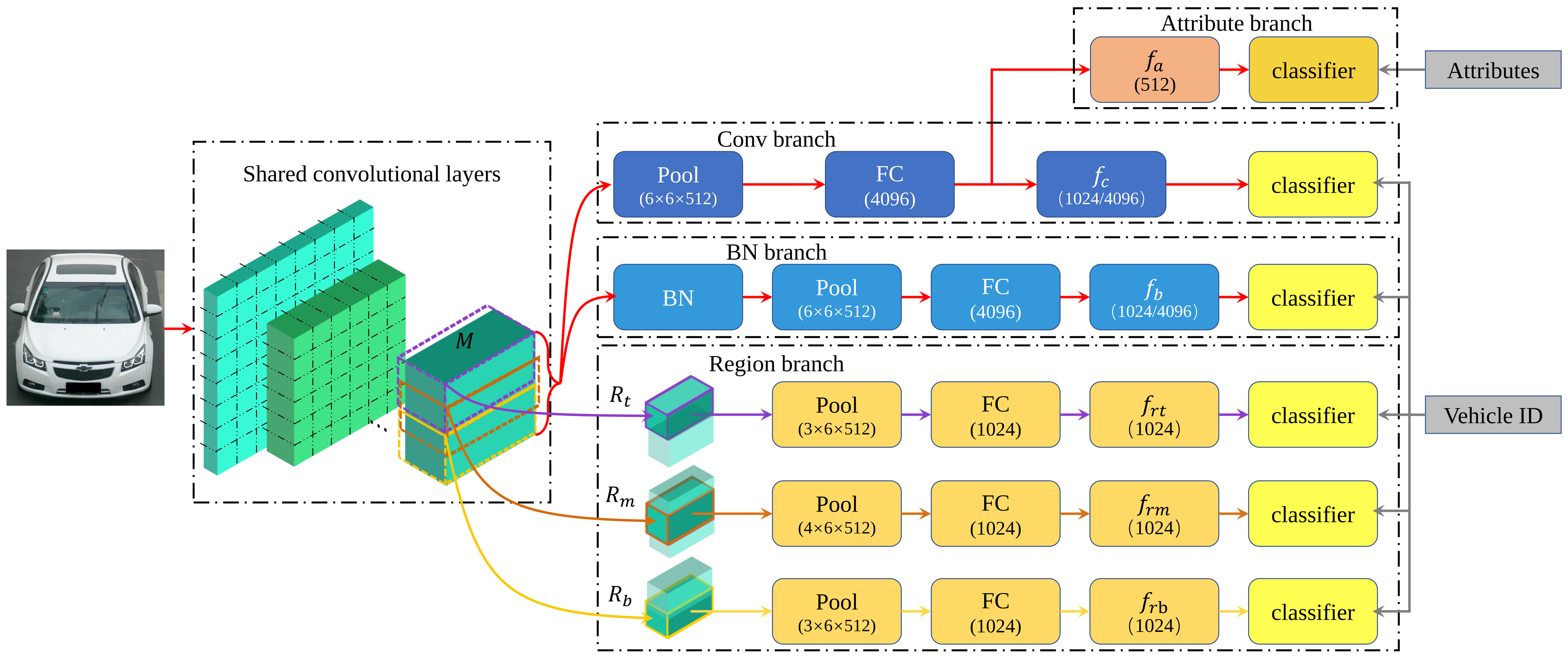
Abstract

- Vehicles of the same model and color commonly share similar global appearance.
- Some local regions may be more distinctive for vehicle Re-ID compared with global appearance.
- We propose a Region-Aware deep Model (**RAM**) to jointly learn global and regional features. This embeds detailed visual cues in local regions.
- Color and model cues are additionally used to jointly train the deep model. This fuses more cues for training and results in more discriminative global and regional features.
- Experiments on two large-scale vehicle Re-ID datasets, *i.e.*, *VeRi* and *VehicleID*, show RAM achieves promising performance.

Different vehicles with similar global appearance. The local differences are highlighted with red circles.

RAM structure



- Conv branch extracts **global** features as previous works do.
- BN branch embeds a BN layer before pooling layer to extract complementary **global** features.
- Region branch extracts **regional** features from three overlapped parts of feature maps.
- Attribute branch extracts **attribute** features learned by attributes classifiers.

Model training

We train the model in a step-by-step manner.
Step-1 first trains the *baseline* model only having the Conv branch.
Step-2 adds the BN branch to the *baseline* model. Model trained in this step is denoted as *BN*.
Step-3 further adds the Region branch to model *BN*. Model trained in this step is denoted as *BN+R*.
Step-4 adds Attribute branch to model *BN+R*. This final model is denoted as *RAM*.

Experiments

1. Performance comparison of features learned by different models on *VeRi*.

Models	mAP	Top-1	Top-5
Baseline	0.550	0.848	0.931
BN	0.581	0.871	0.940
BN+R	0.609	0.887	0.941
RAM	**0.615**	**0.886**	**0.940**

2. Performance comparison of features learned by different models on *VehicleID*.

Models	Top-1			Top-5		
	Small	Medium	Large	Small	Medium	Large
Baseline	0.694	0.673	0.632	0.892	0.820	0.795
BN	0.722	0.705	0.666	0.904	0.853	0.832
BN+R	0.747	0.720	0.674	0.908	0.863	0.842
RAM	**0.752**	**0.723**	**0.677**	**0.915**	**0.870**	**0.845**

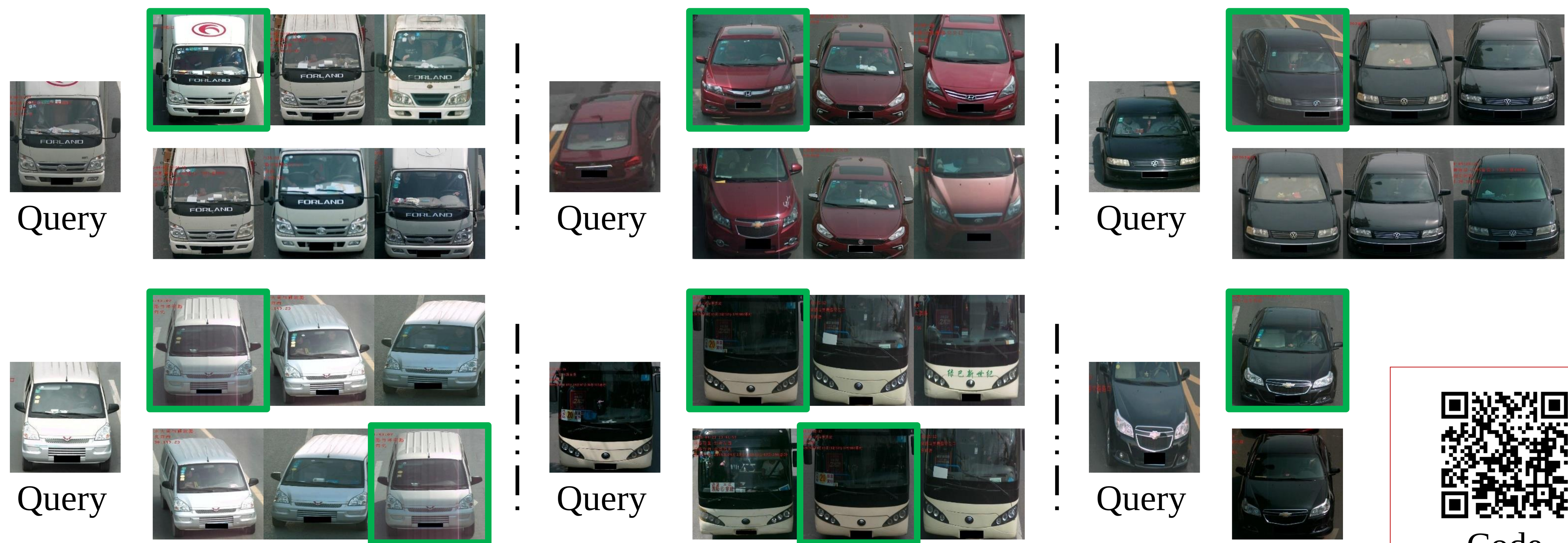
3. Comparison with recent works on *VeRi*.

Models	mAP	Top-1	Top-5
FACT[14]	0.199	0.597	0.753
FPSS[4]	0.278	0.614	0.788
SCPL[5]	0.583	0.835	0.900
OIF[6]	0.480	0.659	0.877
OIF+SF[6]	0.514	0.683	0.897
RAM	**0.615**	**0.886**	**0.940**

4. Comparison with recent works on *VehicleID*.

Models	Top-1			Top-5		
	Small	Medium	Large	Small	Medium	Large
VGGT[3]	0.404	0.354	0.319	0.617	0.546	0.503
VGGCCL[3]	0.436	0.370	0.329	0.642	0.571	0.533
MD+CCL[3]	0.490	0.428	0.382	0.735	0.668	0.616
OIF	-	-	0.670	-	-	0.829
RAM	**0.752**	**0.723**	**0.677**	**0.915**	**0.870**	**0.845**

Examples of returned images on *VehicleID* by *RAM* (in the first line) and *baseline* (in the second line):



Code