Self-Supervised Visual Attention Learning for Vehicle Re-Identification

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Abstract

Visual attention learning (VAL) aims to produce a confidence map as weights to detect discriminative features in each image for certain task such as vehicle re-identification (ReID) where the same vehicle instance needs to be identified across different cameras. In contrast to the literature, in this paper we propose utilizing self-supervised learning to regularize VAL to improving the performance for vehicle ReID. Mathematically using lifting we can factorize the two functions of VAL and self-supervised regularization through another shared function. We implement such factorization using a deep learning framework consisting of three branches: (1) a global branch as backbone for image feature extraction, (2) an attentional branch for producing attention masks, and (3) a self-supervised branch for regularizing the attention learning. Our network design naturally leads to an end-to-end multi-task joint optimization. We conduct comprehensive experiments on three benchmark datasets for vehicle ReID, i.e., VeRi-776, CityFlow-ReID, and VehicleID. We demonstrate the state-of-the-art (SOTA) performance of our approach with the capability of capturing informative vehicle parts with no corresponding manual labels. We also demonstrate the good generalization of our approach in other ReID tasks such as person ReID and multi-target multi-camera tracking.

1 Introduction

Vehicle ReID is a fundamental and challenging problem in video surveillance, because of little discrepancy among the vehicles from identical make and large variations across images of the same instance. The success of recent works suggests that the key to solve this problem is to incorporate explicit mechanisms to discover and concentrate on informative vehicel parts (e.g., wheels, license plate) in addition to capturing robust features from holistic images. They all struggled, however, to annotate original datasets to provide a variety of supervision for training powerful deep convolutional neural networks (CNNs) using, for instance, view segmentation (Meng et al. 2020), keypoints (Khorramshahi et al. 2019; Wang et al. 2017), orientations (Khorramshahi et al. 2019; Wang et al. 2017; Chu et al. 2019) and key parts (He et al. 2019). These annotation processes involve intensive human efforts, and thus significantly restrict the applicability of such approaches.

Visual Attention Learning (VAL). As a useful alternative to avoid manually labeling in computer vision, various VAL approaches such as channel attention (Hu, Shen, and Sun 2018), spatial attention (Woo et al. 2018) and self-attention (Vaswani et al. 2017) have been proposed and demonstrated to be effective in many vision tasks (Fu et al. 2019; Chen et al. 2019a; Khorramshahi et al. 2019; Chen et al. 2019c). For instance, in spatial attention (Woo et al. 2018) the pooling operation is applied to squeeze channel dimension, followed by a convolutional operation on the 2D spatial features, to output attention maps. Intuitively such approaches are advocated in detecting discriminative features to help improve the performance. However, the output attention masks may be too vague to be understandable of why such masks can help improve the performance.

Self-Supervised Learning (SSL). SSL attempts to learn deep representations by exploring intrinsic properties of data (Jing and Tian 2020), and thus provides supervision enhancement to facilitate the learning of downstream tasks. Some works treated SSL as one branch in the multi-task
scheme to boost the performance of the other task. For example, Gidaris et al. (2019) employed SSL as the auxiliary optimization task of few-shot learning to regularize the shared feature encoder. In the literature of unsupervised learning, similar methods also appeared in, e.g., (Chen et al. 2019d), to provide extra supervision for learning the discriminator, which was demonstrated to stabilize the training of GANs effectively.

**Proposed Approach & Contributions.** Motivated by recent works in VAL and SSL, we propose an SSL approach as regularization for VAL to learn attention masks with no extra human labels. Fig. 1 illustrates the differences in the attention masks learned with or without SSL regularization for vehicle ReID. As we see clearly, the attention masks learned with SSL regularization more focus on the critical vehicle parts such as license plate, wheels and corners of vehicle top that can potentially lead to unique features for identifying the instances across not only different cameras but also multiple views (e.g., images with rotations). Conceptually this behavior does make sense, because in order to identify the vehicles from the same make, for instance, successfully detecting such distinguishing parts on the vehicles is the key to solving vehicle ReID.

To regularize VAL in a principle way, mathematically using lifting we factorize the two functions of VAL and self-supervised regularization through another shared function. As an effective instantiation, we propose a deep learning framework to learn discriminative features with attention for vehicle ReID. As we see clearly, the attention masks learned with SSL regularization more focus on the critical vehicle parts such as license plate, wheels and corners of vehicle top that can potentially lead to unique features for identifying the instances across not only different cameras but also multiple views (e.g., images with rotations). Conceptually this behavior does make sense, because in order to identify the vehicles from the same make, for instance, successfully detecting such distinguishing parts on the vehicles is the key to solving vehicle ReID.

In summary, the contributions of our paper are as follows:

- We propose regularizing the visual attention learning using self-supervised learning through lifting. To the best of our knowledge, we are the first to propose such learning mechanism in the literature of visual attention learning.
- We propose a novel network architecture for ReID tasks to generate physically interpretable attention masks as well as improve the performance with discriminative features.
- We demonstrate the SOTA performance for vehicle ReID on VeRi-776 (Liu et al. 2016b), CityFlow-ReID (Tang et al. 2019b) and VehicleID (Liu et al. 2016a).

## 2 Related Works

**Vehicle ReID.** Most of existing works aimed to exploit extra annotations to supervise ReID feature learning. These works can be grouped into three mainstreams as follows: (1) adopting attribute labels (e.g., color and model) (Guo et al. 2019), Yan et al. 2017, Liu et al. 2017, 2016b, 2018, Zhou and Shao 2018) or temporal information (Wang et al. 2017, Shen et al. 2017) to regularize the representation learning; (2) annotating critical parts (He et al. 2019), viewpoint segmentation (Meng et al. 2020), keypoints and vehicle orientation (Khorramshahi et al. 2019, Wang et al. 2017, Chu et al. 2019) to guide local feature extraction; (3) assembling multiple datasets together (Zheng et al. 2020) or synthesizing vehicle images with rich attributes (Lou et al. 2019, Tang et al. 2019a, Wu et al. 2018) to extend training dataset. In addition, there are a couple of works enhancing ReID models from the perspective of metric learning (Chen et al. 2019b, Chu et al. 2019, Bai et al. 2018, Zhang, Liu, and Zhu 2017). Note that vehicle ReID shares many similarities with person ReID for which Ye et al. (2020) conducted a nice survey.

**Visual Attention Learning.** Many visual attention mechanisms have been proposed, e.g., self-attention (Vaswani et al. 2017), channel attention (Hu, Shen, and Sun 2018) and spatial attention (Woo et al. 2018). Some of them have been introduced into the ReID tasks such as (Chen et al. 2019d, Zhou et al. 2019b, Khorramshahi et al. 2019, Chen et al. 2019a, and Zhou et al. 2019b) proposed using attentional gain and multi-level foreground mask consistency to regularize VAL, respectively, while (Wang et al. 2020) adopted equivariant constraints for affine transformation in weakly supervised semantic segmentation for the same purpose. He et al. 2019, Meng et al. 2020 proposed training a second attentional branch based on extra part annotations to recognize interest-of-regions for highlighting the part features by weighting global representations with attention masks. Khorramshahi et al. 2019 proposed filtering annotated keypoints under the guidance of vehicle orientation to focus on such keypoint features. A nice survey on VAL can be found in (Chaudhari et al. 2019) and references therein.

**Self-Supervised Learning.** The success of SSL hinges on devising appropriate pretext task to supervise model learning and a variety of novel tasks have been constructed for, for instance, image generation (Iizuka, Simo-Serra, and Ishikawa 2017), colorization (Zhang, Isola, and Efros 2017), patch position prediction (Doersch, Gupta, and Efros 2015), Kolesnikov, Zhai, and Beyer 2019), patch order classification (Kim, Cho, and Kweon 2019, Kolesnikov, Zhai, and Beyer 2019) and image rotation recognition (Zhai et al. 2019, Feng, Xu, and Tao 2019). Besides, recently contrastive learning of multi-view images (Chen et al. 2020, He et al. 2020) has demonstrated its efficacy. Furthermore, these tasks can also be applied as companion to improve the performance of the main task in multi-task optimization (Gidaris et al. 2019, Chen et al. 2019d). A nice survey on SSL can be found in (Jing and Tian 2020) and references therein.

In contrast to these previous works, we propose regularizing VAL from the perspective of self-supervision, which has not been explored in the literature. We also propose a new deep learning framework for ReID tasks and demonstrate the SOTA performance on vehicle ReID.

## 3 Self-Supervised Visual Attention Learning

### 3.1 Formulation

Given a query image, vehicle ReID aims to predict a ranking list for all gallery images based on the similarity of each pair of query and gallery images. In other words, if two vehicle
characters should be larger that leads to a higher rank. Images are more similar semantically, their feature similarity should be larger that leads to a higher rank.

To learn a proper similarity function, we propose a three-branch framework as illustrated in Fig. 2. Specifically, given an image \( x \in \mathcal{X} \), these branches can be defined as follows:

- **Global Branch** is our backbone and devised to encode robust codes from the whole input image. Its mapping function can be modeled as
  \[
  F_{GB}(x) = g_{GB}(f_{GB}(x), \alpha_{GB}), \beta_{GB})
  \]  
  (1)

  where \( f_{GB} : \mathcal{X} \to \mathcal{T}_1 \) denotes a function, parametrized by \( \alpha_{GB} \), that maps an image into a feature tensor space \( \mathcal{T}_1 \), and \( g_{GB} : \mathcal{T}_1 \to \mathcal{V}_1 \) denotes another function, parametrized by \( \beta_{GB} \), that maps a feature tensor into a vector space \( \mathcal{V}_1 \).

- **Attentional Branch** is responsible for learning attention maps and producing discriminative features locally. Its mapping function can be modeled as
  \[
  F_{AB}(x) = g_{AB}(f_{GB}(x), \alpha_{GB}) \odot f_{AB}(h(x, \alpha_{AB}), \beta_{AB})
  \]  
  (2)

  where \( h : \mathcal{X} \to \mathcal{T}_2 \) denotes a function, parametrized by \( \alpha_{AB} \), to map an image into another tensor space \( \mathcal{T}_2 \), \( f_{AB} : \mathcal{T}_2 \to \mathcal{M} \) denotes a function to map a feature tensor into an attention mask space \( \mathcal{M} \) with the same spatial dimension as \( \mathcal{T}_1 \), \( g_{AB} : \mathcal{T}_1 \to \mathcal{V}_2 \) denotes a function, parametrized by \( \beta_{AB} \), to map a feature tensor into another vector space \( \mathcal{V}_2 \), and \( \odot \) denotes the entry-wise multiplication operation.

- **Self-supervised Branch** regularizes its learning of the attentional branch by sharing the attention encoder. Its mapping function can be modeled as
  \[
  F_{SB}(x') = g_{SB}(h(x'), \alpha_{AB}), \beta_{SB})
  \]  
  (3)

  where \( g_{SB} : \mathcal{T}_2 \to \mathcal{V}_3 \) is a function, parametrized by \( \beta_{SB} \), to map a feature tensor into a third vector space \( \mathcal{V}_3 \), and \( x' \) denotes a new image by transforming \( x \) (e.g., rotation).

**Regularization Perspective from Lifting.** From Eq. 2 and Eq. 3 we can clearly see that \( F_{AB}, F_{SB} \) share a common function \( h \). This indicates that the change of \( h \) will has a significant impact on both functions, and vice versa. Therefore, the learning of parameter \( \alpha_{AB} \) is controllable by both functions, rather than only \( F_{AB} \) in conventional VAL.

In fact, from the same lifting perspective, we can easily see that in terms of functionality \( F_{AB} \) in Eq. 2 also enforces the regularization on \( F_{GB} \) in Eq. 1 through a shared function \( f_{GB} \). Considering the model complexity and data complexity in ReID tasks, such regularization is very important in learning, where the attentional branch plays a key role to connect the other two independent branches smoothly as a bridge. In our experiments, we demonstrate that GB+AB performs better than GB, and GB+AB+SB further improves the performance. Such empirical evidences support our understanding on regularization in learning.

**Learning Objective.** Given a training set \( \{(x_i, y_i)\}_{i \in I} \) where \( (x_i, y_i) \in \mathcal{X} \times \mathcal{Y}, \forall i \) denotes a pair of an image and its ID label, respectively, we denote \( s_{ij} = \phi(F_{GB}(x_i), F_{AB}(x_i), F_{GB}(x_j), F_{AB}(x_j)) \) as the similarity between images \( x_i, x_j \) defined by function \( \phi \). We then propose optimizing the following problem to learn the model:

\[
\min_{\alpha, \beta, \gamma} \sum_{i \in I} \mathcal{L}_1(F_{GB}(x_i), F_{AB}(x_i), y_i, \gamma_1)
+ \sum_{i,j,k \in I} \mathcal{L}_2(s_{ij}, s_{ik}, y_i, y_j, y_k)
+ \sum_{i \in I} \mathcal{L}_3(F_{SB}(x'_i), y'_i, \gamma_2)
\]  
(4)

where \( \alpha = \{\alpha_{GB}, \alpha_{AB}\}, \beta = \{\beta_{GB}, \beta_{AB}, \beta_{SB}\}, \gamma = \{\gamma_1, \gamma_2\} \) denote the learnable parameters. \( \mathcal{L}_1 \) denotes an ID loss with parameter \( \gamma_1 \), \( \mathcal{L}_2 \) denotes a triplet loss, \( \mathcal{L}_3 \) denotes a self-supervised loss with parameter \( \gamma_2 \), \( y'_i \) denotes pseudo label of \( x'_i \), and \( \lambda_1, \lambda_2 \geq 0 \) denote two predefined scalars. Note that only the triplet loss \( \mathcal{L}_3 \) is defined based on the image similarity to enforce \( s_{ij} = s_{ik} \) if \( y_i = y_j \neq y_k \).

**Inference for ReID.** Given \( \{x_p\}_{p \in P}, \{x_q\}_{q \in Q} \) as sets of gallery and query images, respectively, we need to predict a ranking list of \( x_q \)'s for every \( x_p \) based on the learned similarity function \( s \). We retrieve Top-1 or Top-K gallery images to evaluate our approach using different metrics such as accuracy and mean average precision (mAP).

### 3.2 Instantiation using Deep Neural Networks

Fig. 2 illustrates an instantiation of our approach using deep learning, where each subnetwork with a unique color represents one of the functions in Eq. 1, Eq. 2 and Eq. 3 and these learnable weights refer to the parameters \( \alpha, \beta \) in Eq. 4.

We list the network architectural details as follows:

- **Attention Computing Module (ACM).** We illustrate the ACM in Fig. 3 where \( L \in \mathbb{R}^{c \times h \times w} \) defines a 3D tensor feature from a lightweight network similar to D2-Net (Dusmanu et al. 2019), and \( c, h, w \) denote the channel, height and width dimension, respectively. Then softmax normalization.
over neighborhood of each point is conducted along each channel in $L$, i.e., $M(k,u,v) = \exp(L(k,u,v)) \sum_{(m,n) \in N((u,v))} \exp(L(k,m,n))$, where $N(u,v)$ denotes neighborhood set with size $K$ around location $(u,v)$ along the $k$-th channel. Meanwhile, non-maximum suppression across all the channels is conducted in $L$ as well, i.e., $G(k,u,v) = \max_{t=1,\ldots,T} L(t,u,v)$. To amplify the informative signal effectively, we obtain our soft mask $Q$ by $Q(u,v) = \sum_{(m,n)} Q(m,n)$ where $Q(u,v) = \max_{t=1,\ldots,T} \{M(t,u,v) : G(t,u,v)\}$.

**Batch Normalization (BNNeck).** Luo et al. [2019] proposed this network for ReID by adding a batch normalization layer (BN) without bias term between the GAP and the fully connected (FC) layer as well as removing bias term in FC. Empirically it was demonstrated that BNNeck can improve the inconsistency between the triplet loss and the ID loss during training, leading to better generalization.

**Self-Supervised Branch.** In general, SSL is equivalent to supervised learning with pseudo labels, and often taken as an auxiliary task together with the original learning task. Motivated by recent works such as Feng et al. [2019], Kolesnikov et al. [2019], and Wojke and Bewley [2018], we propose to add image rotation degrees as pseudo labels for prediction based on the cosine classifier (CC) (Gidaris et al. 2019). Specifically, to prepare the auxiliary data and labels, we rotate each training image by $0^\circ$, $90^\circ$, $180^\circ$ or $270^\circ$ and assign 0, 1, 2 or 3 as its pseudo label accordingly.

**Other Architectural Details.** Same as most of the ReID works, we choose ResNet50 (He et al. 2016) as our model backbone, with $\text{stride} = 2$ in $\text{conv5}$.x replaced with $\text{stride} = 1$ to output larger feature maps (Chen et al. 2019c, Luo et al. 2019). In the **Global Branch**, the backbone is divided into two phases: the first phase ($\text{conv}1$, $\text{conv}2$.x, $\text{conv}3$.x) and second phase ($\text{conv}4$.x, $\text{conv}5$.x). In the **Attentional Branch**, the backbone is modified as the attention encoder by setting $\text{stride} = 1$ in $\text{conv}4$.x, $\text{conv}5$.x to extract local features. By passing through it, each image is only downsampled by 8 times so that attention can be computed in a larger space. Then the local discriminative features after entry-wise multiplication are fed into $\text{conv4}$.x', $\text{conv5}$.x', holding identical architectures with $\text{conv4}$.x, $\text{conv5}$.x in ResNet50, for further process. In the **Self-supervised Branch**, the features from the shared sub-network are fed into another subnetwork consisting of two basic blocks (He et al. 2016) (with $\text{stride} = 2$ in the first convolutional layer).

### 3.3 Training & Testing

To train our network, we utilize the hard mining triplet loss (Tri) (Hermans et al. 2017) and the smoothed cross-entropy (SCE) loss (Sze et al. 2016), that are widely used in the ReID tasks. We also choose the negative Euclidean distance as our similarity measure.

**Implicit Data Augmentation in Training.** To better explain this, we list the hard mining triplet loss as below:

$$L_{\text{Tri}}(x, \mathcal{X}_{PN}) = \left[ \tau - \min_{p=1,\ldots,P} s(F(x), F(x_p)) \right]_{+} + \max_{n=1,\ldots,N} s(F(x), F(x_n))$$

where $x$ denotes an image, $\{x_p\} \subset \mathcal{X}_{PN}$ denote the positive image set with the same ID as $x$, $\{x_n\} \subset \mathcal{X}_{PN}$ denote the negative image set with different IDs, $s$ denotes the similarity function, $F$ denotes the feature extraction function, and $[\cdot]_{+}$ denotes the nonnegative operator with a constant margin $\tau$. Note that this loss aims to maximize the margin between minimum positive similarity and maximum negative similarity for better discriminability among features.

In our network training, we propose applying this triplet loss, as well as the SCE loss, to the global branch and the attentional branch separately, rather than taking the concatenation of $F_{GB}, F_{AB}$ as a feature vector $F$ for training. In this way, there is much more flexibility in choosing the positive and negative pairs for both branches in the loss that can come from different images. Such image mixture from both branches allows our training to exploit more “images” implicitly for better generalization.

Finally we define our overall loss function as

$$L_{\text{overall}} = \lambda_{\text{Tri}}^{\text{GB}} L_{\text{Tri}}^{\text{GB}} + \lambda_{\text{SCE}}^{\text{GB}} L_{\text{SCE}}^{\text{GB}} + \lambda_{\text{Tri}}^{\text{AB}} L_{\text{Tri}}^{\text{AB}} + \lambda_{\text{SCE}}^{\text{AB}} L_{\text{SCE}}^{\text{AB}} + \lambda_{\text{rot}} L_{\text{rot}},$$

where $L_{\text{rot}}$ denotes the CE loss based on the cosine classifier for the self-supervised branch. To avoid heavy tuning of the hyperparameters, we simply set $\lambda_{\text{Tri}}^{\text{GB}}, \lambda_{\text{SCE}}^{\text{GB}}, \lambda_{\text{Tri}}^{\text{AB}}, \lambda_{\text{SCE}}^{\text{AB}}$ to 0.5 and $\lambda_{\text{rot}}$ to 1.0 in all the experiments. Only $\lambda_{\text{rot}}$ is fine-tuned in our ablation study.

**ReID Testing.** At the test stage, the self-supervised branch is deactivated for inference. Following the suggestions in Luo et al. [2019], we normalize the concatenation vector of $F_{GB}, F_{AB}$ for each image as the feature vector, and use the Euclidean distance for ranking. In fact, similar to Luo et al. [2019], we observe that empirically such $\ell_2$-normalized features can improve the performance by $\sim 1\%$ over different combinations of training and testing approaches, including training with the feature concatenation. In our experiments, we report the performance of the network in Fig. 2 using the normalized features.

### 4 Experiments

**Datasets.** We conduct comprehensive experiments on three benchmark datasets for vehicle ReID. VeRi-776 (Liu et al. 2018), and...
CityFlow-ReID (Tang et al. 2019b) is a challenging dataset where images are captured by 40 cameras under diverse environments. 36,935 images from 333 identities form the training set and the testing set contains 18,290 images from the other 333 vehicles. VehicleID (Liu et al. 2016a) is a large-scale benchmark containing 221,763 images of 26,267 vehicles. All images are taken from front or rear view. The gallery set only contains one randomly selected image for each testing identity, and thus here we report our results as the mean over 10 trials. In this dataset there are three numbers of gallery images widely used for testing, i.e., 800 (small), 1600 (medium) and 2400 (large).

**Training & Evaluation Protocols.** During training, random cropping, horizontally flipping and erasing are performed as data augmentation strategies. None of them is adopted to process testing images. All images are resized to 256 × 256. We choose PyTorch to implement our model and adopt Adam optimizer (Kingma and Ba 2014) with default betas (β₁ = 0.9, β₂ = 0.999), weight decay 5e-4 to optimize it. All experiments are conducted on one NVIDIA GEFORCE RTX 2080Ti GPU. The training batch size on VeRi-776 and CityFlow-ReID is 28 and on VehicleID is 40 with 4 images from each instance. On VeRi-776 and CityFlow-ReID, the initial learning rate is 1e-4 and the margin of triplet loss is set as τ = 0.5 empirically. The number of training epochs is 80 and the learning rate decreases by multiplying 0.1 at epoch 20, 40, 60, respectively. On VehicleID, the margin is τ = 0.7 and the number of learning epochs is 120. The learning rate increases linearly from 0 to 1e-4 during the first 10 epochs, decreases by cosine scheduler to 1e-7 at 100th epoch and to 0 at the last epoch.

At test time we evaluate our approach using 4 widely used metrics in the ReID tasks, i.e., image-to-track retrieval mAP (tmAP) if tracks are available in the data, image-to-image retrieval mAP (imAP), Top-1 and Top-5 accuracy. We show these metric numbers as percentages and the best are marked in bold. Following the literature of ReID, e.g., (Meng et al. 2020; He et al. 2019; Chen et al. 2019c), we report our best performance on each dataset with no cross-validation.

### 4.1 State-of-the-art Performance Comparison

**VeRi-776.** We list our comparison results in Table 1 with recent SOTA algorithms, i.e., Siamese+Path (Shen et al. 2017), OIFE and OIFE+ST (Wang et al. 2017), VAMI (Zhou and Shao 2018), NuFACT (Liu et al. 2017), AAVER (Khorramshahi et al. 2019), RS and R+MT+K (Tang et al. 2019a), VANet (Chu et al. 2019), SAN (Qian et al. 2020a), PART (He et al. 2019), PVEN (Meng et al. 2020), DMML (Chen et al. 2019b). We can see that most of recent methods utilized extra labels. For instance, VANet annotated 5,000 images from VeRi-776 and VehicleID, respectively, to train a viewpoint predictor and learned distinct metrics for similar or dissimilar viewpoint pairs. AAVER relied on predefined keypoint and orientation prediction to guide the learning of discriminative features. Also, SAN adopted various attribute labels to supervise its attribute-aware branch. Besides, PART defined three types of vehicle parts, i.e., front and back lights, front and back windows, and vehicle brand, as objects to optimize YOLO in an offline manner. When training the ReID model, they extracted local features from detected locations by YOLO as supplementary information for global representations. In PVEN, they provided part segmentation ground-truth based on viewpoint visibility for 3,165 images from VeRi-776 to train a U-Net parser. They implemented part-aware feature alignment using the mask produced from the segmentor. In contrast, our model does not need any additional annotations to assist local feature learning. Although, due to GPU limitation, our training batch size 28 on VeRi-776 is much smaller than other methods (e.g., 256 in SAN), our method can still outperform the other competitors significantly in terms of tmAP, imAP and Top-1 accuracy. On Top-5 accuracy ours is only 0.5% lower than the best that uses image size of 512 × 512 for training.

**CityFlow-ReID.** We compare our method with FVS (Tang et al. 2018), RS and R+MT+K (Tang et al. 2019a), Xent, Htri, Cent and Xent+Htri (Zhou and Xiang 2019), BA and BS (Kuma et al. 2019) in Table 2. This dataset is very challenging because images are taken from 5 scenarios, covering a diverse set of location types, various scenes and traffic

| Method       | EI | tmAP | imAP | Top-1 | Top-5 |
|--------------|----|------|------|-------|-------|
| Siamese+Path | Y  | 58.27| -    | 83.49 | 90.04 |
| OIFE         | Y  | 48.0 | -    | 65.9  | 87.7  |
| OIFE+ST      | Y  | 51.42| -    | 68.3  | 89.7  |
| VAMI         | Y  | 50.13| -    | 77.03 | 90.82 |
| NuFACT       | Y  | 53.42| -    | 81.56 | 95.11 |
| AAVER        | Y  | 58.52| -    | 88.68 | 94.10 |
| RS           | Y  | -    | 63.76| 90.70 | 94.40 |
| R+MT+K       | Y  | -    | 65.44| 90.94 | 96.72 |
| VANet        | Y  | 66.34| -    | 89.78 | 95.99 |
| SAN          | Y  | 72.5 | -    | 93.3  | 97.1  |
| PART         | Y  | 74.3 | -    | 94.3  | 98.7  |
| PVEN         | Y  | -    | 79.5 | 95.6  | 98.4  |

### Table 1: Result comparison on VeRi-776, where EI is short for extra information for stronger supervision in learning.

| Method       | EI | imAP | Top-1 | Top-5 |
|--------------|----|------|-------|-------|
| FVS          | Y  | 5.08 | 20.82 | 24.52 |
| RS           | Y  | 25.66| 50.37 | 61.48 |
| R+MT+K       | Y  | 30.57| 54.56 | 66.54 |
| Xent         | N  | 18.62| 39.92 | 52.66 |
| Htri         | N  | 24.04| 45.75 | 61.24 |
| Cent         | N  | 9.49 | 27.92 | 39.77 |
| Xent+Htri    | N  | 25.06| 51.69 | 62.84 |
| BA           | N  | 25.61| 49.62 | 65.02 |
| BS           | N  | 25.57| 49.05 | 63.12 |
| Ours         | N  | 37.14| 60.08| 67.21 |

### Table 2: Result comparison on CityFlow-ReID.
Table 3: Results comparison on VehicleID.

| Method | VeRi-776 imAP | CityFlow-ReID imAP | Top-1 | Top-5 |
|--------|---------------|---------------------|-------|-------|
| GB w/o attention | 84.0 | 78.3 | 32.0 | 56.27 |
| GB+ResNet18 w/o attention | 85.2 | 79.5 | 34.63 | 57.98 |
| GB+AB (K = 7) | 85.9 | 80.7 | 36.63 | 59.98 |
| GB+AB (K = 11) | 85.8 | 80.6 | 35.94 | 59.70 |
| GB+AB (K = 15) | 85.5 | 80.2 | 36.32 | 58.56 |
| GB+AB+SB (λ_{rot} = 0.1) | 85.8 | 80.5 | 36.61 | 59.13 |
| GB+AB+SB (λ_{rot} = 1.0) | 86.2 | 80.9 | 37.14 | 60.08 |
| GB+AB+SB (λ_{rot} = 2.0) | 86.1 | 80.9 | 36.54 | 59.60 |
| GB+AB+SB (λ_{rot} = 3.0) | 85.9 | 80.7 | 36.89 | **60.36** |
| GB+AB+SB (λ_{rot} = 10.0) | 85.9 | 80.5 | 36.54 | 59.13 |

Table 4: Experimental results for our ablation study, where we underline the selected parameters for K in ACM and λ_{rot} in Eq. [6]. The performance improvement upon each component is observed consistently across the datasets.

We conduct three experiments with different K to explore the effect of neighborhood size on the performance while fixing the other hyperparameters. Note that such attention operations are conducted on 8x downsampled feature maps rather than the original image size whose actual receptive field is 64K^2. Compared with the baseline using GB alone, we can see substantial improvements on all the metrics, especially for the challenging CityFlow-ReID dataset. Such improvements are relatively robust w.r.t. K, and we set K = 7 by default in our experiments. Note that by comparing “GB+AB” with “GB+ResNet18 w/o attention” we can conclude that a good attention mechanism is much more important than a similar larger backbone in GB.

Further Improvement from SB with Tradeoff Parameter λ_{rot}. To choose a proper coefficient for the self-supervised loss L_{rot}, we evaluate λ_{rot} within different scales to perform comparison while fixing the other hyperparameters. It is clear that self-supervised learning with λ_{rot} = 1.0 boosts ReID performance further on all the metrics across both datasets. Again the small performance fluctuations with largely different λ_{rot} suggest the robustness of our method.

It is worth mentioning that such performance improvements from either AB or SB or both essentially come from our attention mechanism that helps regularize GB as well as AB, leading to significantly better generalization in the training of our network.
4.4 Generalization to Other ReID Tasks

In this section we will demonstrate the potentials of using our approach in person ReID and multi-target multi-camera (MTMC) tracking that are highly related to vehicle ReID.

**Person ReID.** Rather than identifying individual vehicles, this task aims to identify the same person in images from different cameras. We conduct some experiments on Market-1501 (Zheng et al. 2015), a widely used benchmark dataset for person ReID. Our training details keep identical to those on VehicleID. Our approach can achieve 86.1%, 94.3% and 98.3% in terms of imAP, Top-1 and Top-5 accuracy, respectively, which are comparable or even better than recent methods (Zheng et al. 2019; Zhou et al. 2019a). We also visualize the learned attention masks in Fig. 5. Surprisingly, with no extra labels of body parts, our approach can manage to consistently align the masks well with the body parts such as head, arms and legs, similar to our observations in Fig. 4.

**MTMC Tracking.** Given the tracklets of multiple targets in the videos from different cameras, this task aims to synchronize such tracklets with the same target across the cameras, *i.e.*, ReID with tracklets rather than images. We conduct our experiments on the dataset used in City-Scale Multi-Camera Vehicle Tracking in AI City Challenge 2020 (Tang et al. 2019c). Similar to (Qian et al. 2020b), we simply adopt an efficient MTMC tracking pipeline. Specifically, we firstly use the pre-trained Mask R-CNN (He et al. 2017) to detect vehicles from each video frame. Then we use Deep SORT (Wojke, Bewley, and Paulus 2017) with association strategy from (Wang et al. 2019) to perform online multi-target single camera vehicle tracking. Now we directly apply our vehicle ReID model pre-trained on VeRi-776 (with visible license plates) without fine-tuning to synchronize such separate tracklets by re-identifying the vehicle instance of each tracklet across multi-camera videos. We list our comparison in Table 5 where, as of writing this paper, our result achieves rank 1 in the leaderboard that is significantly better than the second best.

In summary, we believe that our approach can be well generalized to other ReID tasks, with the capability of consistently locating discriminative features for the same instance across different scenarios using attention masks.

5 Conclusion

In this paper we propose a novel deep learning framework for vehicle ReID by learning the visual attention masks for generating discriminative features, both globally and locally. We introduce self-supervised learning (SSL) to better regularize the visual attention learning (VAL) through a shared function in lifting. Based on this, we propose an effective instantiation using deep neural networks that consists of global, attentional and self-supervised branches. We evaluate it on three benchmarks for vehicle ReID. Our results can always achieve comparable to, or even better than, the current SOTA. We also generalize our approach to other ReID related tasks such as person ReID and multi-target multi-camera tracking with good performances. Visualization verifies the effectiveness of our attention masks.
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