Supplementary Materials

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1 Viewpoint Based Experiments

Our VA-reID method addresses the viewpoint variations effectively and outperforms the state-of-the-art supervised Re-ID methods. In the main text, we have presented the excellent performance of the VA-reID method on all test set of Market-1501 and DukeMTMC-reID. Further, we want to evaluate the performance of **single-viewpoint pedestrian matching** and **cross-viewpoints pedestrian matching**. Therefore, we construct two viewpoint based test sets in Market-1501.

1.1 Single-Viewpoint Pedestrian Matching

At first, we merge the query set and test set of Market-1501 and get a new images set $\mathbf{D}$. Then, according to the viewpoint label, we divide $\mathbf{D}$ into three small sets,$\mathbf{D}_{front}$, $\mathbf{D}_{side}$, $\mathbf{D}_{back}$, respectively. And we experiment on the three small sets separately. Take $\mathbf{D}_{front}$ as an example, we need to construct new query set and gallery set. We randomly select one image of each person and put it into the new query set. Other images form the new gallery set. We will repeat the random splitting process for 10 times and calculate the average Rank1/Rank5 and mAP.

From Table 1, we observe that our VA-reID method outperforms the baseline method on all datasets. For images from the same viewpoint, the VA-reID method can learn the discriminative feature representation.

Table 1: Results (%) of single-viewpoint pedestrian matching.

Dataset	Method	mAP	Rank-1	Rank-5
$\mathbf{D}_{front}$	baseline	91.59	94.30	98.11
	VA-reID	93.40	95.54	98.05
$\mathbf{D}_{side}$	baseline	93.76	95.62	97.97
	VA-reID	92.83	95.16	98.66
$\mathbf{D}_{back}$	baseline	93.73	95.69	98.27
	VA-reID	92.49	94.90	97.94

Table 2: Results (%) of cross-viewpoint pedestrian matching.

Query	Gallery	Method	mAP	Rank-1	Rank-5
$\mathbf{D}_{front}$	$\mathbf{D}$ - $\mathbf{D}_{front}$	baseline	86.10	90.85	94.88
		VA-reID	89.79	93.43	96.46
$\mathbf{D}_{side}$	$\mathbf{D}$ - $\mathbf{D}_{side}$	baseline	86.90	94.90	98.21
		VA-reID	89.68	96.36	98.67
$\mathbf{D}_{back}$	$\mathbf{D}$ - $\mathbf{D}_{back}$	baseline	86.85	94.86	98.20
		VA-reID	89.64	96.33	98.66

1.2 Cross-Viewpoint Pedestrian Matching

Similarly, we merge the query set and test set of Market-1501 and get a new images set $\mathbf{D}$. According to the viewpoint label, we divide $\mathbf{D}$ into three small sets,$\mathbf{D}_{front}$, $\mathbf{D}_{side}$, $\mathbf{D}_{back}$, respectively. We design three experiments: (1) using $\mathbf{D}_{front}$ as query set and $\mathbf{D} - \mathbf{D}_{front}$ as gallery set; (2)using $\mathbf{D}_{side}$ as query set and $\mathbf{D} - \mathbf{D}_{side}$ as gallery set; (3) using $\mathbf{D}_{back}$ as query set and $\mathbf{D} - \mathbf{D}_{back}$ as gallery set. The result is shown in Table 2.

From Table 2, we observe that our VA-reID method outperforms the baseline method on all three cases. Whether we use images from the front viewpoint to match images from side and back viewpoints, or use images from side viewpoint to match images from front and back viewpoints, or use images from the back viewpoint to match images from front and side viewpoints, the VA-reID method achieves excellent performance.

2 Complexity Analysis.

We compare the complexity of our method with the state-of-the-art methods. Two metrics, Flops and Params, are calculated by a tool(Lyken17 2019) call Thop for pytorch-based models. From Table 5, we can observe that VA-reID model owns less Flops and Params than MGN, Pyramid, ABD-Net but outperforms them. Although VA-reID model our model owns the same backbone network as SRB(Luo et al. 2019), it achieves a significant improvement by 1.97%/0.85% on mAP/Rank-1 accuracy in Market-1501 dataset.

Table 3: Complexity comparisons to the state-of-the-art methods in Market-1501 dataset. Flops(G): floating-point operations per second. Params(M):parameters of network.

Method	Flops(G)	Params(M)	Market-1501	
			mAP	Rank-1
MGN	11.96	70.35	86.9	95.7
SRB	9.85	48.45	88.0	95.0
Pyramid	9.80	54.84	88.2	95.7
ABD-Net	14.07	69.18	88.28	95.60
VA-reID	9.86	52.64	89.97	95.87

References

Luo, H.; Gu, Y.; Liao, X.; Lai, S.; and Jiang, W. 2019. Bag of tricks and a strong baseline for deep person re-identification. In *The IEEE Conference on Computer Vision and Pattern Recognition Workshops*.

Lyken17. 2019. Thop: Pytorch-opcounter. https://github.com/Lyken17/pytorch-OpCounter/. Accessed April 4, 2010.