

Supplementary Materials: Cloth-aware Augmentation for Cloth-generalized Person Re-identification

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1 EXPERIMENTS

The Effects of Consisting Components. We further assess the efficacy of Domain Augmentation and Feature Augmentation with AGW [3] and MGN [2] baselines, demonstrating that our module serves as an easily integratable enhancement for models, resulting in improved generalization ability. Our experiments are conducted using the LTCC dataset, and the results of the general setting are summarized in Table 1. It is evident that our strategy consistently enhances the overall generalization ability of other methods, seamlessly integrating into existing frameworks. Additionally, we perform experiments with CAL to showcase the performance of inner-sample and inter-sample exchanging in Table ??, demonstrating the positive impact of both strategies on generalization ability and robustness.

The Augmentation Strategy Comparison. As shown in Table 3, the results indicate that our strategy effectively mitigates the potential issue of augmenting data with poor quality. Moreover, our domain augmentation approach saves computational resources by utilizing a frozen model and serves as an efficient integration strategy for various augmentation techniques.

Parameter Analysis. We further investigate the parameter m , which governs the probability of exchanging elements in the feature augmentation strategy, as illustrated in Figure 1. The results demonstrate a significant improvement in performance once the feature augmentation strategy is applied to the Baseline. We determine that setting $m=0.2$ yields optimal performance.

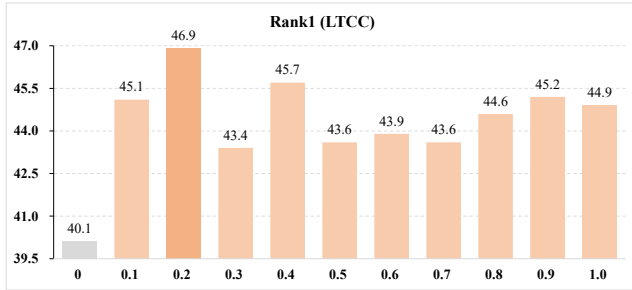


Figure 1: The parameter analysis for exchanging elements.

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Table 1: Ablation studies on different components of our method in LTCC with the AGW and MGN Baseline.

AGW	MGN	\mathcal{L}_{D-Aug}	\mathcal{L}_{F-Aug}	General	
				Rank1	mAP
-	✓	-	-	68.4	34.6
-	✓	✓	-	71.2	34.8
-	✓	✓	✓	71.8	35.7
✓	-	-	-	71.8	34.9
✓	-	✓	-	74.5	36.6
✓	-	✓	✓	75.4	37.1

Table 2: Ablation studies on Feature Augmentation in LTCC with the CAL Baseline.

Inner-sample	Inter-sample	General		Cloth-changing	
		Rank1	mAP	Rank1	mAP
-	-	74.2	40.8	40.1	18.0
-	✓	76.5	44.6	43.4	24.6
✓	✓	78.1	46.4	46.9	26.5

Table 3: The Comparison with Other Augmentation Strategies in LTCC with the AGW Baseline.

Strategy	General	
	Rank1	mAP
Domain Augmentation	73.3	36.3
Feature Augmentation	74.7	36.5
Mixed Augmentation	75.4	37.1
CutOut [1]	72.6	34.7
CutMix [4]	72.2	34.9
Mixup [5]	72.4	34.7
Erasing [6]	72.4	33.9

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