Rethinking ReID: Multi-Feature Fusion Person Re-identification Based On Orientation Constraints

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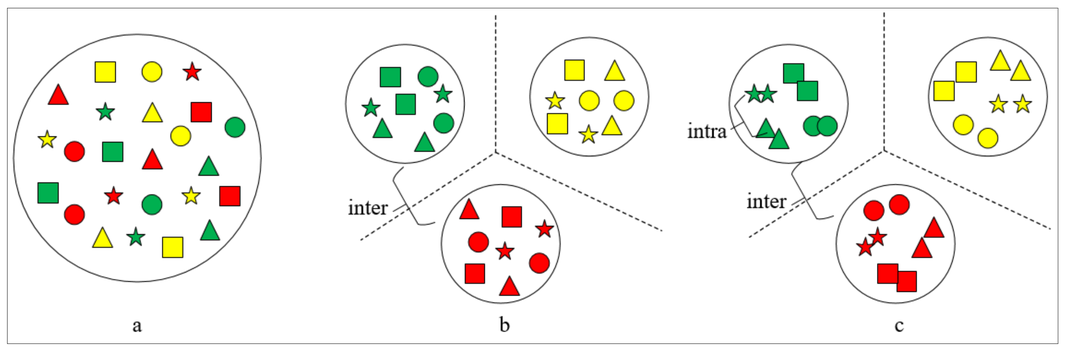
1 Introduction

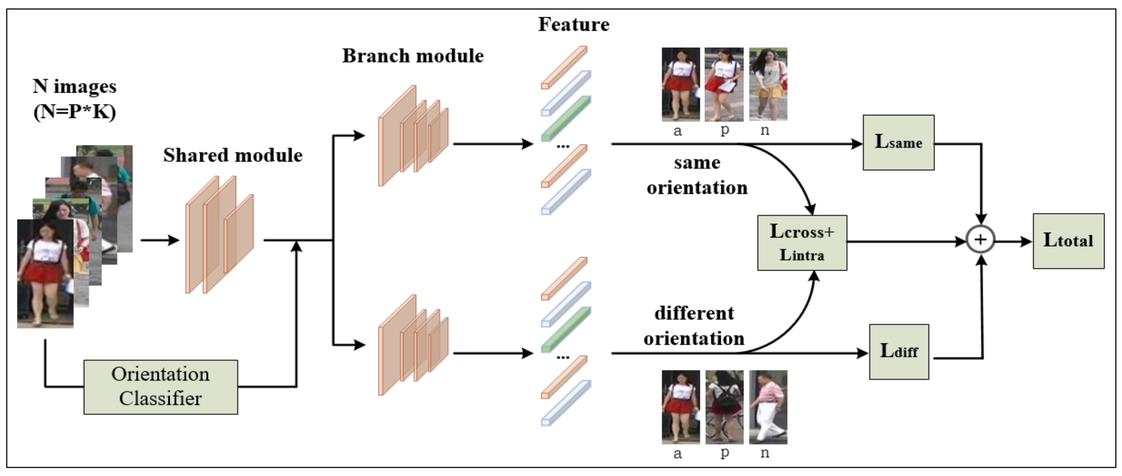
- **Question:** Various targets in the same body orientations look too similar to distinguish by the model, while the same subject viewed in different orientations looks rather different. How to overcome the influence of differences in orientation?
- **Motivation:**
  - ✓ Adding orientation constraint in ReID network design.
  - ✓ The robustness of features is enhanced by distinguishing orientation.
- **Contributions:**
  - ✓ A sampling strategy for selecting training samples based on orientation is proposed, which increases the difficulty of the triples.
  - ✓ We propose a multi-feature fusion network model based on orientation constraints and a hybrid loss function training strategy.
  - ✓ We propose a pedestrian orientation identification method based on local features, which can obtain the orientation label of each image.

2 Design Idea of Our Method



- Our network can not only distinguish different people, but also form perspective-level clusters, so that the model can preferentially identify the person with same orientation.
- The method not only has competitive performance on multiple datasets, but also can let retrieval results aligned with the orientation of the query sample rank higher.

3 Method



- **A. Orientation-based sample sampling strategy**

  Randomly select P persons for each training batch. But in the selection of K images of each person, ensure that there are both samples with the same orientation and samples with different orientations in the K images.

$$L_{triHard} = \frac{1}{P*K}\sum_{a\in batch}[\max d(a,p) - \min d(a,n) + \alpha]_+$$

- **B. Training strategy (hybrid loss function)**

  1). Same-orientation branch.

$$L_{same} = L_{triSame} + L_{ceSame} + \lambda L_{center}$$

  2). Different-orientation branch.

$$L_{diff} = L_{triDiff} + L_{ceDiff} + \lambda L_{center}$$

  3). Cross-constrained training.

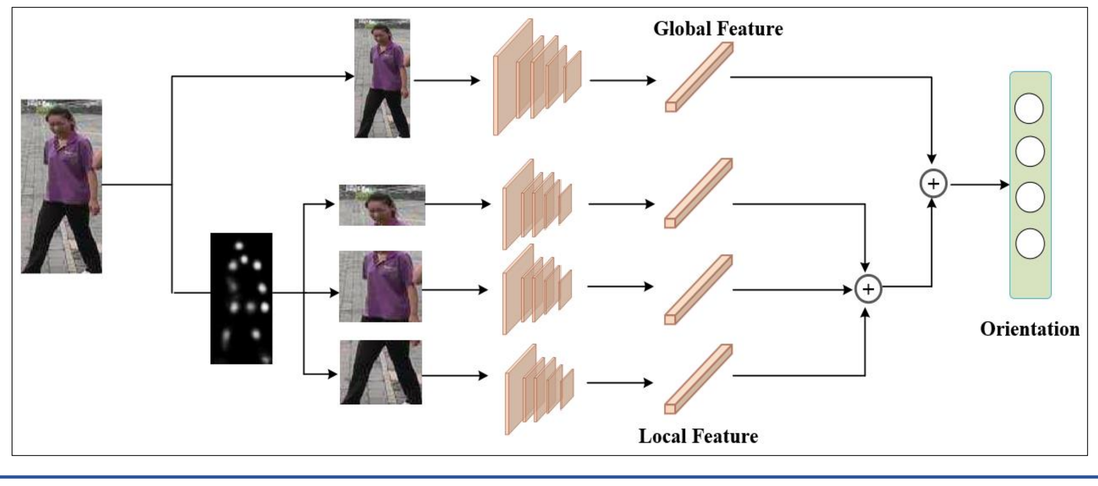
$$L_{cross} = \frac{1}{P*K}\sum_{a\in batch}[\max d(a,pd) - \min d(a,ns) + \theta]_+$$

$$L_{intra} = \frac{1}{P*K}\sum_{a\in batch}[\max d(a,ps) - \min d(a,pd) + \delta]_+$$

- **C. Global and Local Feature Fusion**

  We use the AlignedReID method to obtains body parts through horizontal division, and realize automatic alignment based on the shortest path. In conjunction with global features, we have added local feature triples to both the upper and lower branches for auxiliary training, while still using only global features during the testing phase.

- **D. The Design of Orientation Classifier**



4 Results

Methods	Market-1501		
	Rank-1(%)	*Rank-5(%)*	*mAP(%)*
PCB	92.3	97.2	77.4
AlignedReID	91.8	97.1	79.3
PIE	87.33	95.56	69.25
GLAD	89.9	-	73.9
Spindle	76.9	91.5	-
HA-CNN	91.2	-	75.7
TriHard	86.67	93.38	81.07
HPM	94.2	97.5	82.7
PGR	93.87	97.74	77.21
OSCNN	83.9	-	73.5
OCMFPR(ours)	**94.71**	**98.06**	**84.11**
OCMFPR(ours+RR)	**94.87**	**98.30**	**92.71**

Methods	DukeMTMC-ReID		
	Rank-1(%)	*Rank-5(%)*	*mAP(%)*
PCB	81.7	89.7	66.1
AlignedReID	81.2	-	67.4
PIE	80.84	88.30	64.09
HA-CNN	80.5	-	63.8
HPM	86.6	-	74.3
PGR	83.63	91.66	65.98
SVDNet	76.7	-	56.8
OCMFPR(ours)	**87.31**	**93.54**	**73.20**
OCMFPR(ours+RR)	**90.63**	**94.25**	**87.67**