Body Part-based Representation Learning for Occluded Person Re-Identification

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GitHub Link

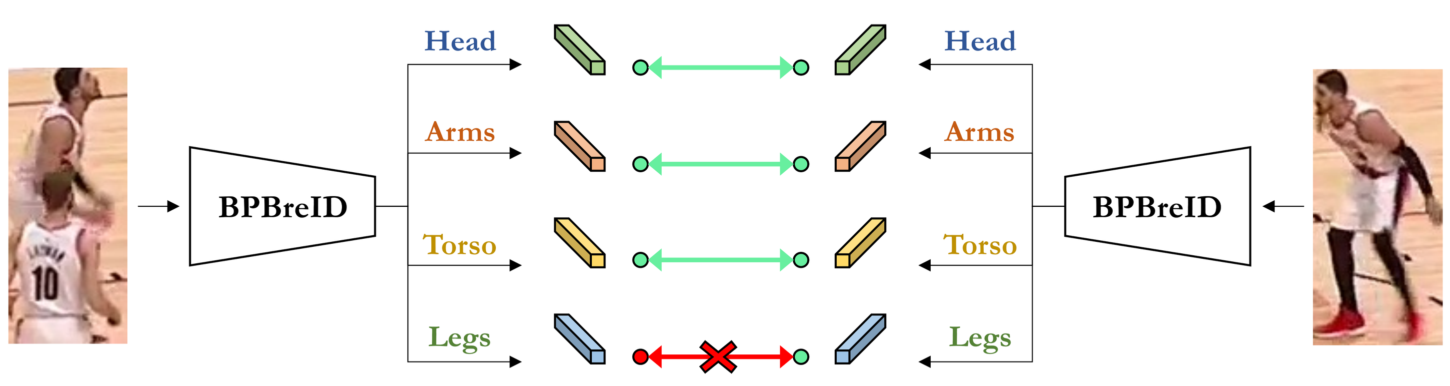
Overview

In this work, we propose **BPBreID**, a part-based method for **occluded person re-identification**.

We make two contributions:

1. An **attention module** to extract one feature vector for each **body part.**
2. The **GiLt loss**, a novel loss to train any part-based method.

Part-based ReID method:



Motivations

Training part-based methods is **challenging**:

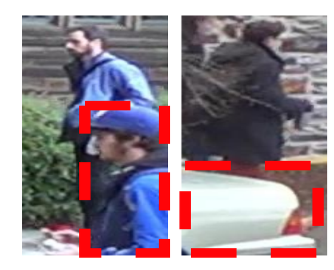
Challenge 1

ReID datasets do not provide **human parsing** labels

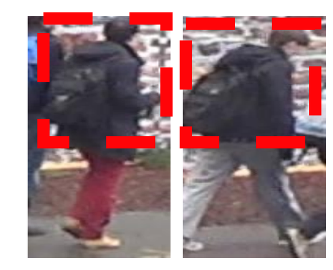
Information from **external model** is inaccurate

Challenge 2

Local representation learning with ID labels is tricky



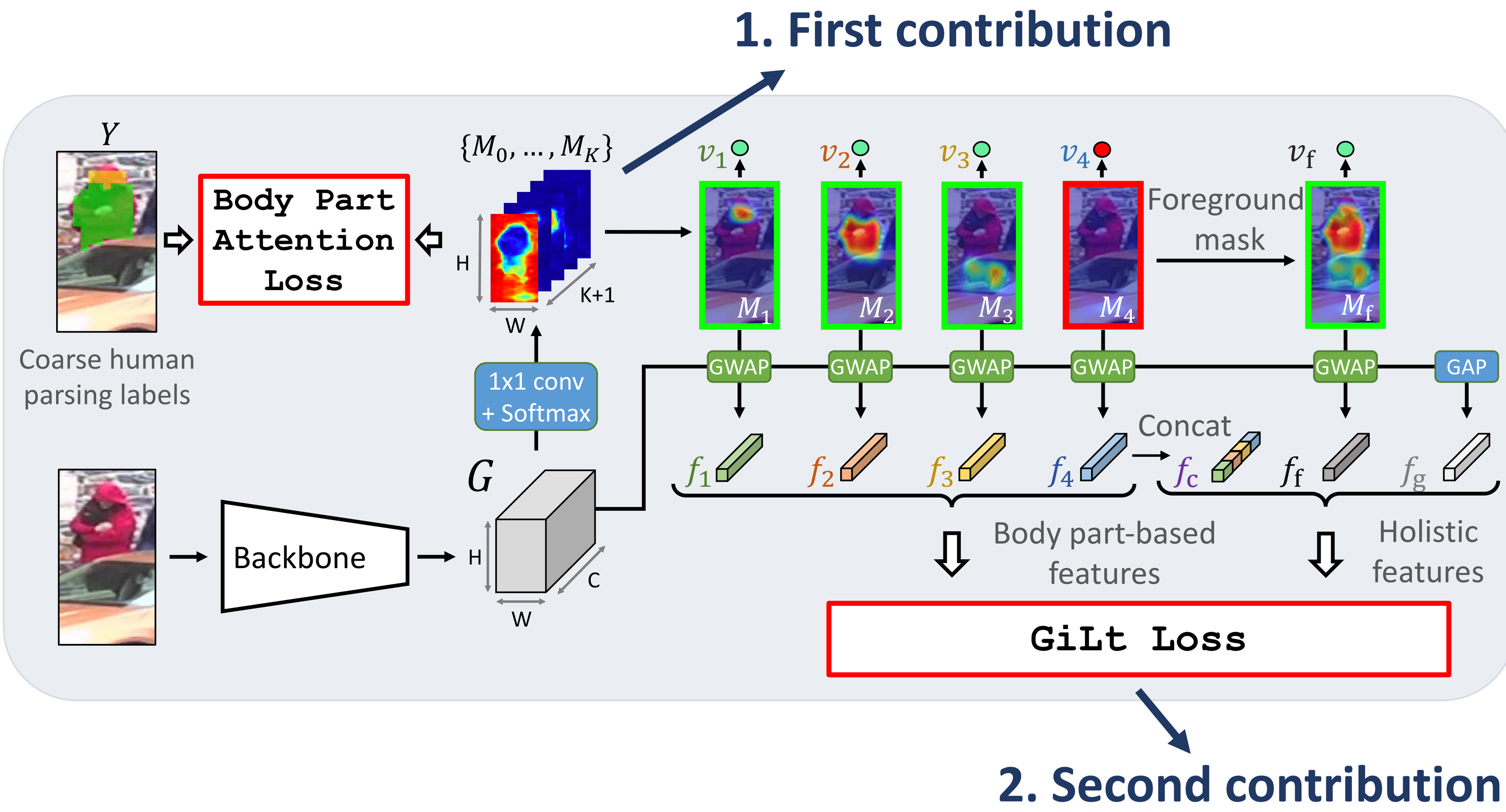
Some parts might be **occluded**



Some parts are **non-discriminative**

Our proposed method: BPBreID

Overview of the **architecture** of our model. **BPBreID** outputs **K** body **part-based** embeddings and three **holistic** embeddings.

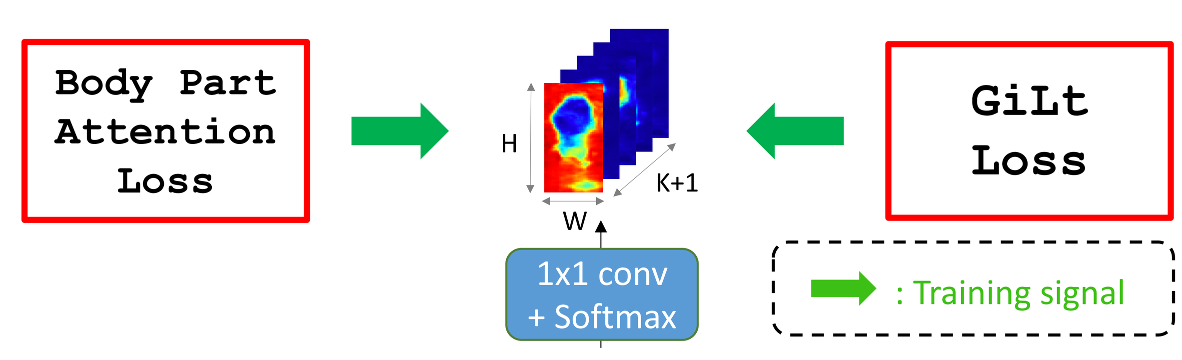


Our coarse human parsing labels

ReId relevant body part attention maps from our model for K=5

1. Body parts attention module

Two training signals, from both the **ReID objective** and the **part prediction objective**. Learned attention is more **accurate** and **ReID specialized**!



2. GiLt loss

GiLt stands for **Global-identity Local-triplet**. Robust to **occlusions** and **non-discriminative** parts, because has always access to **global information** for solving the **Re-ID objective**.

$$L_{GiLt} = L_{id} + L_{tri} = \sum_{i \in \{g,f,c\}} L_{CE}(f_i) + \underbrace{L_{tri}^{parts}(f_1, ..., f_K)}$$

$$d_{parts}^{ij} = \frac{\sum_{k=1}^{K} dist_{eucl}(f_k^i, f_k^j)}{K}$$

Distance function used for the triplet loss

Performance

Comparison of BPBreID with **SOTA** methods:

Methods	Holistic datasets				Occluded datasets					
	Market -1501		DukeMT -MC-ReID		Occluded -Duke		Occluded -reID		P-Duke -MTMC	
	R-1	mAP	R-1	mAP	R-1	mAP	R-1	mAP	R-1	mAP
PVPM [3] ‡	-	-	-	-	-	-	66.8	59.5	85.1	69.9
HOReID [5] ‡	94.2	84.9	86.9	75.6	55.1	43.8	80.3	70.2	-	-
ISP [46] ‡	95.3	88.6	89.6	80.0	62.8	52.3	-	-	-	-
PAT [13] ‡	95.4	88.0	88.8	78.2	64.5	53.6	81.6	72.1	-	-
PGFL [40] ‡	95.3	87.2	89.6	79.5	63.0	54.1	80.7	70.3	81.1	64.2
HPNet [9] ‡	-	-	-	-	-	-	**87.3**[1]	77.4[3]	-	-
SSGR [31] †	**96.1**[1]	89.3	91.1	81.3	69.0	57.2	78.5	72.9	-	-
FED [29] †	95.0	86.3	89.4	78.0	68.1	56.4	86.3[2]	79.3[2]	-	-
LDS [35] †	95.8[2]	**90.3**[1]	91.5[3]	82.5[3]	64.3	55.7	-	-	91.9[2]	82.9[2]
PFD [28] ‡	95.5	89.7[2]	91.2	83.2[2]	69.5[3]	61.8[2]	81.5	**83.0**[1]	-	-
$BPBreID_{RI}$ ‡	95.7	88.4	91.7[2]	81.3	71.3[2]	57.5[3]	77.0	70.9	91.3[3]	79.2[3]
$BPBreID_{HR}$ ‡	95.7[3]	89.4[3]	**92.4**[1]	**84.2**[1]	**75.1**[1]	**62.5**[1]	82.9[3]	75.2[4]	**93.0**[1]	**83.2**[1]

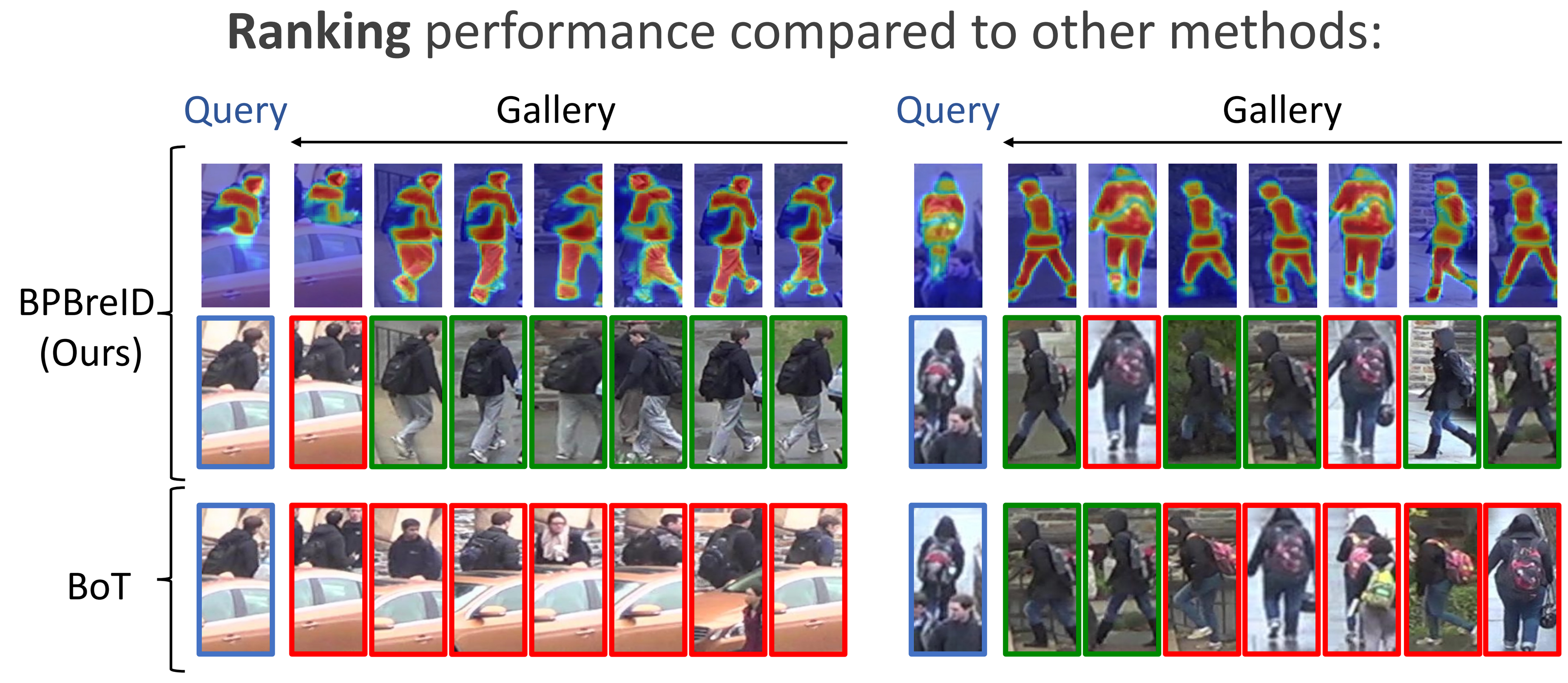
Experiments

Ablation study of BPBreID:

Methods	R-1	mAP
BoT [14] baseline	51.4	44.7
BPBreID	**66.7**	**54.1**
- w/o learnable attention	51.6	39.2
- w/o visibility scores	52.6	45.3
- w/o GiLt loss	57.2	43.2
- w/o part-averaged triplet loss	64.8	51.7

Visualization

Ranking performance compared to other methods:



Individual vs **all** body parts ranking:

Attention **heatmaps**: