Domain Consistency Representation Learning for Lifelong Person Re-Identification

Shiben Liu, Huijie Fan*, Qiang Wang, Weihong Ren, BaojieFan, Yandong Tang

***Abstract*—Lifelong person re-identification (LReID) exhibits a contradictory relationship between intra-domain discrimination and inter-domain gaps when learning from continuous data. Intra-domain discrimination focuses on individual nuances (*i.e.*, clothing type, accessories, *etc.*), while inter-domain gaps emphasize domain consistency. Achieving a trade-off between maximizing intra-domain discrimination and minimizing inter-domain gaps is a crucial challenge for improving LReID performance. Most existing methods strive to reduce inter-domain gaps through knowledge distillation to maintain domain consistency. However, they often ignore intra-domain discrimination. To address this challenge, we propose a novel domain consistency representation learning (DCR) model that explores global and attribute-wise representations as a bridge to balance intra-domain discrimination and inter-domain gaps. At the intra-domain level, we explore the complementary relationship between global and attribute-wise representations to improve discrimination among similar identities. Excessive learning intra-domain discrimination can lead to catastrophic forgetting. We further develop an attribute-oriented anti-forgetting (AF) strategy that explores attribute-wise representations to enhance inter-domain consistency, and propose a knowledge consolidation (KC) strategy to facilitate knowledge transfer. Extensive experiments show that our DCR model achieves superior performance compared to state-of-the-art LReID methods. Our code will be available soon.**

***Index Terms*—Lifelong learning, person re-identification, domain consistency representations, attribute and text guided representations.**

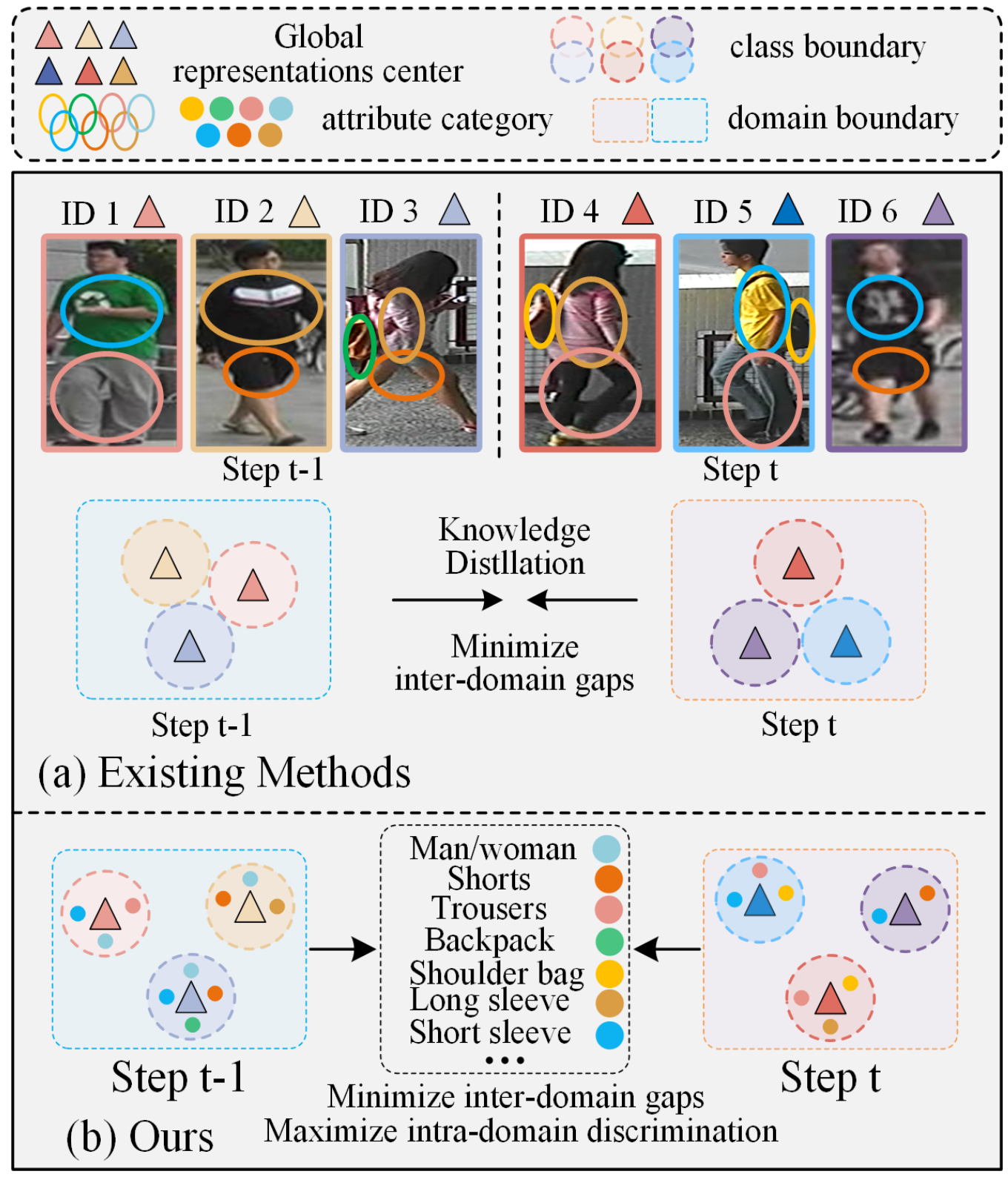

Fig. 1. Comparison between our method and existing methods. (a) Existing methods [1, 2] leverage knowledge distillation to minimize inter-domain gaps but ignore intra-domain discrimination, which limits the LReID model's ability to learn new knowledge. (b) Our method explores attribute-wise representations as a bridge to achieve a trade-off between maximizing intra-domain discrimination and minimizing inter-domain gaps, enhancing the LReID model's anti-forgetting and generalization capabilities.

I. Introduction

Person re-identification (ReID) aims to retrieve the same individual across non-overlapping cameras in a large-scale database, and has achieved significant progress using uni-modal architectures such as convolutional neural networks (CNN) [3, 4] or vision transformers (ViT) [5–7]. However, when ReID models are applied to continuous datasets collected by dynamic monitoring systems, they exhibit notable performance limitations. Thus recent works have focused more on the practical problem of lifelong person re-identification (LReID), which involves learning from streaming data and maintaining strong performance across all data.

At present, lifelong person re-identification (LReID) suffers from the challenge of balancing the anti-forgetting of old knowledge and learning new knowledge. Specifically, there are two main issues to solve this challenge. 1) **Intra-domain discrimination**. Each identity may exhibit subtle nuances of individual information (*i.e.*, clothing type, accessories, haircut, *etc.*) and lead to severe distribution overlapping. Learning discriminative representations of individuals are effective for distinguish identity information. 2) **Inter-domain gaps**. The dataset of each task is collected in different illumination and background, leading to inter-domain gaps. Bridging intra-

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Shiben Liu is with the State Key Laboratory of Robotics, Shenyang Institute of Automation, Chinese Academy of Sciences, Shenyang 110016, China, and with the University of Chinese Academy of Sciences, Beijing 100049, China (e-mail: liushiben@sia.cn).

Huijie Fan, and Yandong Tang are with the State Key Laboratory of Robotics, Shenyang Institute of Automation, Chinese Academy of Sciences, Shenyang, 110016, China (e-mail: fanhuiie@sia.cn; ytang@sia.cn).

Qiang Wang is the Key Laboratory of Manufacturing Industrial Integrated in Shenyang University Shenyang 110044, China (e-mail: wangqiang@sia.cn).

Weihong Ren is the Harbin Institute of Technology, Shenzhen 518055, China (e-mail: renweihong@hit.edu.cn).

Baojie Fan is with the Department of Automation college at Nanjing University of Posts and Telecommunications, Nanjing 210000, China. (e-mail: jobfbj@gmail.com).

domain gaps are significant for mitigating catastrophic forgetting in LReID.

To address these issues, we aim to learn consistency representations that capture individual nuances in intra-domain and inter-domain consistency in LReID, striking a balance between maximizing intra-domain discrimination and minimizing inter-domain gaps. Knowledge distillation-based approaches [2, 8–10] ensure distribution consistency between the previous and current datasets to alleviate catastrophic forgetting. However, these approaches impose strict constraints and ignore intra-domain discrimination, [11–13], as outlined in Figure 1(a). While LReID models significantly improve intra-domain discrimination for the current step, they inevitably damage inter-domain consistency, leading to catastrophic forgetting. Thus, we propose consistency representations as a bridge to achieve a trade-off between maximizing intra-domain discrimination and minimizing inter-domain gaps, improving the anti-forgetting and generalization capabilities of the LReID model, as illustrated in Figure 1(b).

Specifically, we propose a novel domain consistency representation learning (DCR) model, which first explores attribute and text information to enhance LReID performance. Unlike methods [14–16], we develop consistency representations including global and attribute-wise representations to capture individual nuances in intra-domain and inter-domain consistency in LReID. We design an attribute-text generator (ATG) to dynamically generate text-image pairs for each instance, which are then fed into a text-guided aggregation (TGA) network to improve the global representation capability, effectively distinguishing identities in LReID. In addition, the attributes of each instance guide an attribute compensation (ACN) network to generate attribute-wise representations focusing on specific regional information of identities. We consider that attributes can ensure reliability by setting higher thresholds across datasets. Therefore, the generated attribute-wise representations and text for each instance are considered reliable in our model.

In summary, we explore global representations and attribute-wise representations to strike a balance between maximizing identity-discriminative information of intra-domain and minimizing inter-domain gaps. At the intra-domain discrimination level, global representations capture whole-body information, while attribute-wise representations focus on specific regional information. When whole-body appearances or attribute-related information are very similar across identities, we combine global and attribute-wise representations to distinguish among similar identities, maximizing intra-domain discrimination. Perfect learning intra-domain discrimination can lead to catasttophic forgetting. We further develop an attribute-oriented anti-forgetting (AF) strategy that explore attribute-wise representations for bridging inter-domain gaps across continuous datasets. Additionally, knowledge consolidation (KC) is proposed to enable knowledge transfer, improving generalization capabilities. Our contributions are as follows:

- We propose a novel domain consistency representation learning (DCR) model that explores global and attribute-wise representations to capture individual nuances in intra-domain and inter-domain consistency, achieving a trade-off between maximizing intra-domain discrimination and minimizing inter-domain gaps.
- In the intra-domain context, we explore the complementary relationship between global and attribute-wise representations to enhance the discrimination of each identity and adapt to new knowledge.
- In the inter-domain context, we design an attribute-oriented anti-forgetting (AF) and a knowledge consolidation (KC) strategy to minimize inter-domain gaps and facilitate knowledge transfer, improving the LReID model's generalization and anti-forgetting capabilities.

A. Lifelong Person Re-Identification

Lifelong Person Re-Identification (LReID) faces a formidable challenge, aiming to address the evolving nature of person identification across various scenarios. Some works [12, 17] are proposed to tackle the issue of adapting ReID models over time while retaining knowledge gained from previous distribution. Generally, Pu *et al.* [17] proposed learnable knowledge graphs that adaptively facilitate the mutual exchange of new and old knowledge, thus achieving knowledge accumulation. Some works [1, 8, 9, 14] aim to extract rich and discriminative representation, mitigating the risk of knowledge forgetting. Pu *et al.* [8] proposed a meta reconciliation normalization (MRN) for mining meta-knowledge shared across different domains. Meanwhile, ConRFL [9] maintains learnable and consistent features across all seen domains, which improves the discrimination and adaptation ability of the LReID model. In addition, some methods [1, 2, 17] mitigate catastrophic forgetting and enhance model accuracy by using rehearsal-based strategies with images stored from previous tasks. These approaches strive to reduce inter-domain gaps, ensuring distribution consistency across datasets to mitigate catastrophic forgetting. However, this strategy employs strict constraints and ignores intra-domain discrimination, limiting LReID model's performance to learn new knowledge. In this paper, we propose consistency representations as a bridge to achieve a trade-off between maximizing intra-domain discrimination and minimizing inter-domain gaps for improving the anti-forgetting and generalization capabilities of the LReID model.

B. Vision-Language for Person Re-Identification

The vision-language learning paradigms [18–20] have gained considerable popularity in recent years. Contrastive Language-Image Pre-training (CLIP) [21], establishes a connection between natural language and visual content through the similarity constraint of image-text pair. CLIP has been applied to multiple person re-identification tasks [22, 23], including text-to-image, text-based single-modality, text-based cross modality. Text-to-image methods [24–26] aims to retrieve the target person based on a textual query. Text-based single-modality works [5, 6] leverage text descriptions to generate robust visual features or to integrate the beneficial features of text and images for the person

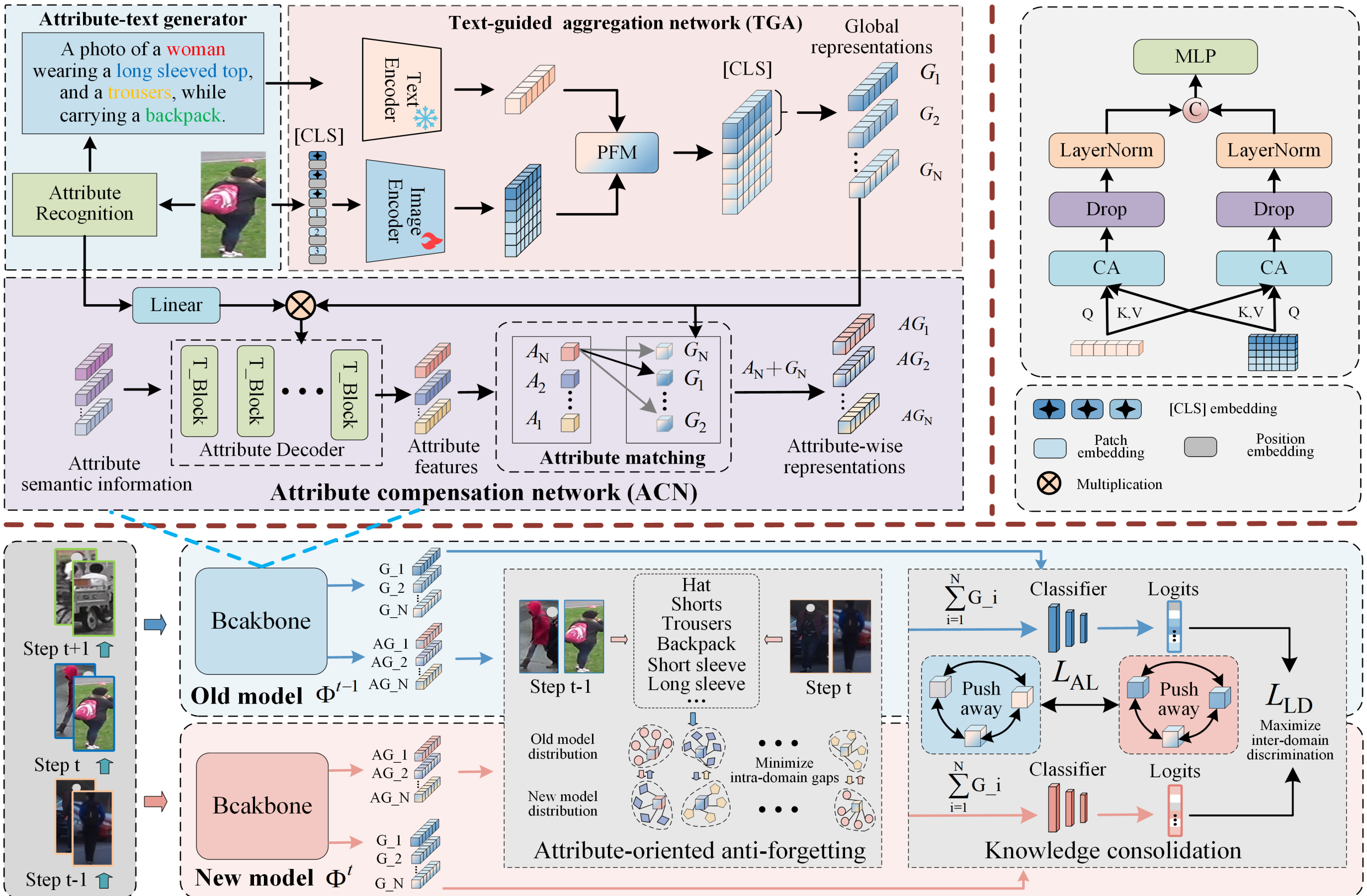

Fig. 2. Overview of the proposed DCR for LReID. First, the attribute-text generator (ATG) dynamically generates text-image pairs for each instance. Then, the text-guided aggregation network (TGA) captures global representations for each identity, while the attribute compensation network (ACN) generates attribute-wise representations. We explore the complementary relationship between global and attribute-wise representations to maximize intra-domain discrimination. Meanwhile, we design attribute-oriented anti-forgetting (AF) and knowledge consolidation (KC) strategies to minimize inter-domain gaps and facilitate knowledge transfer.

category. Text-based cross modality methods [27] employ text descriptions to alleviate visible-infrared modality gaps. Text infromation generated by prompt learning and text inversion, providing insufficient text descriptions of each identity. In this paper, we dynamically generate text-image pairs from single image to capture fine-grained global representations based on the CLIP model for improving inter-domain discrimination.

C. Pedestrian Attribute Recognition

Pedestrian attribute recognition aims to assign a set of attributes (Gender, Bag, Short/Long sleeve, and *etc.*) to a visual representation of a pedestrian. Deep learning-based researches [28] automatically learn hierarchical features from raw images, improving recognition accuracy. Multi-task learning approaches [29–31] leverage additional contextual information of across tasks, such as pedestrian detection or pose estimation, to significantly improve attribute recognition. Part-based methods [32, 33] divide the pedestrian image into several parts or regions, providing more accurate attribute localization. At present, the above methods have achieved significant success in improving the accuracy of attribute recognition. We are the first to explore the application of attributes to LReID from the following two aspects. 1) Attributes are converted into text descriptions for each image to enhance global representation capabilities. 2) Attributes are transformed into attribute-wise representations by specific networks to maximize intra-domain discrimination and minimize intra-domain gaps.

II. Proposed Method

A. Preliminary: Overview of Method

The overview of our DCR model to achieve a trade-off between maximizing intra-domian discrimination and minimizing inter-domain gaps, is depicted as Figure 2. The DCR model learns the old model Φ^{t-1} and new model Φ^{t} from (t-1)-th and t-th steps, where Φ^{t} is inherited from Φ^{t-1}. Φ^{t-1} and Φ^{t} with three branches of attribute-text generator (ATG), text-guided aggregation network (TGA) and attribute compensation network (ACN). ϕ^{t-1} and ϕ^{t} serve as classifier heads for the old and new models, providing logits of each instance for recognition. Additionally, we define that consecutive T person datasets $D = \{D^t\}_{t=1}^{T}$ are collected from different environments, and establish a memory buffer M to store a limited number of samples from each previous ReID dataset.

Given an image $x_i^t \in \mathcal{D}^t \cup \mathcal{M}$, we forward it to Φ^{t-1} and Φ^t is as follows:

$$G^{t-1}, AG^{t-1} = \Phi^{t-1}(x^i); \quad G^t, AG^t = \Phi^t(x^i). \tag{1}$$

B. Attribute-Text Generator

Due to the lack of text-image pairs in ReID datasets, we propose an attribute-text generator (ATG) to dynamically generate corresponding text descriptions for each instance. Specifically, we first introduce an attribute recognition model pre-trained on the PA100K dataset [35] to generate attribute categories (*i.e.*, female, backpack, short/long sleeve, and *etc.*), which are then converted into text descriptions for each instance using a specific template. This template adds modifiers (in black font) to each attribute (in a different color font) to create a complete sentence describing an instance, as shown in Figure 2. Although, attributes can vary significantly across datasets, we consider that text descriptions can be made reliable by setting a higher threshold (Confidence threshold=0.80) to ensure classification accuracy of attribute recognition network.

C. Text-Guided Aggregation Netwrok

We propose a text-guided aggregation network (TGA) to explore global representations for each identity and knowledge transfer, as shown in Figure 2 (TGA). The TGA includes a CLIP model and a parallel fusion module (PFM). Note that the text encoder is frozen in our DCR model.

Parallel Fusion Module. By attribute-text generator obtain text-image pairs, we employ CLIP with text encoder $\mathcal{T}(\cdot)$ and image encoder $\mathcal{V}(\cdot)$ to extract text and image embedding, respectively. Unlike CLIP [21], we introduce multiple [CLS] embeddings into the image encoder input sequence to capture multiple global representations from different perspectives. To obtain fine-grained global representations for improving the performance of the LReID model, we propose a parallel fusion module (PFM) to explicitly explore the interactions between image embeddings and text embeddings, as shown in Figure 2 (PFM). Firstly, we leverage text embedding d^* as query and image embedding $[v_1^*, \cdots, v_N^*, v_1, \cdots, v_P]$ as key and value to implement operation with cross-attention, drop, and layer normalization, getting text-wise representations. Similarly, in another fusion branch, image-wise representations are obtained. Finally, image-wise and text-wise representations perform concatenation and MLP operations to obtain global representations $G^t = \{G_i | i = 1, 2, \cdots, N\}$, focusing on whole body information. We force multiple global reprsentatios G^t at the current step to learn more discriminative information by orthogonal loss to minimize the overlapping elements. The orthogonal loss can be formulated as:

$$L_{Ort} = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (G_i^t, G_j^t) \tag{2}$$

Then, we utilize the cross-entropy loss L_{CE} and triplet loss L_{Tri}^g [6] to optimize our DCR at the current task.

$$L_{\mathrm{CE}} = \frac{1}{K} \sum_{i=1}^{K} y_i \log((\phi^t(G^t))_i) \tag{3}$$

$$L_{\mathrm{Tri}}^g = max(d_p^g - d_n^g + m, 0) \tag{4}$$

where K is the number of classes, and m is the margin, d_p^g and d_n^g are the distances from positive samples and negative samples to anchor samples in global representations, respectively. Unlike some methods [2, 11], global representations generated by the text-guided aggregation (TGA) network present two advantages. First, we leverage text descriptions based on the CLIP model to enhance the discrimination capability of global representations, allowing them to better distinguish identities and adapt to new knowledge. Second, global representations facilitate knowledge transfer, improving the model's generalization ability.

D. Attribute Compensation Network

We force attributes to guide attribute compensation network (ACN) for learning attribute-wise representations. The ACN consists of an attribute decoder and an attribute matching component, as illustrated in Figure 2 (ACN).

Attribute Decoder. Enabling attributes to better adapt across datasets, we define multiple learnable attribute semantic information $A^* = \{A_i^* | i = 1, 2, \cdots, N\}$ to learn discriminative information. The attributes undergo a linear layer to increase its dimensions, and then multiplies with the text-image global representation to output f_{AT}. Attribute semantic information A^* as queries Q, f_{AT} as keys and values are input into attribute decoder, which outputs the attribute features $A = \{A_i | i = 1, 2, \cdots, N\}$. The attribute decoder employs six transformer blocks (T_Block) referenced from [36].

Attribute Matching. The attribute features $A = \{A_i | i = 1, 2, \cdots, N\}$ learn multiple discriminative local infromation of individuals. However, it is unclear which attribute features correspond to specific body parts. Thus, we propose an attribute matching (AM) component to associate attribute features and global representations $G = \{G_i | i = 1, 2, \cdots, N\}$. The core objective is to find the most similar global representations$G$ from different perspectives and local attribute features A, and then add the them with the highest similarity. Specifically, attribute-wise representations $AG^t = \{AG_i | i = 1, 2, \cdots, N\}$ is formulated as:

$$k = argmax(\frac{< A_i, G >}{|A_i||G|}) \tag{5}$$

$$AG_i = A_i + G_k. \tag{6}$$

We leverage the triplet loss to align attribute-wise representations with identity at the current step, assisting in global representations to distinguish similar identities.

$$L_{\mathrm{Tri}}^l = max(d_p - d_n + m, 0) \tag{7}$$

where, d_p^l and d_n^l are the distances from positive samples and negative samples to anchor samples in attribute-wise representations, respectively. In this paper, attribute-wise representations that contain specific information of individuals assist global representations in distinguishing similar identities for maximizing intra-domain discrimination. Meanwhile, attribute-wise representations as a bridge across increasing datasets to minimize inter-domain gaps for better knowledge transfer.

TABLE I
PERFORMANCE COMPARISON WITH STATE-OF-THE-ART METHODS ON TRAINING ORDER-2. BASELINE MODEL INCLUDES CLIP MODEL AND ATTRIBUTE-TEXT GENERATOR. BOLD AND RED FONTS ARE OPTIMAL AND SUBOPTIMAL VALUES, RESPECTIVELY. TRAINING ORDER-1 IS MARKET→CUHK-SYSU→ DUKEMTMC→MSMT17_V2→CUHK03.

Method	Market1501		CUHK-SYSU		DukeMTMC		MSMT17_V2		CUHK03		Seen-Avg		Unseen-Avg	
	mAP	R-1	mAP	R-1	mAP	R-1	mAP	R-1	mAP	R-1	mAP	R-1	mAP	R-1
AKA[17]	58.1	77.4	72.5	74.8	28.7	45.2	6.1	16.2	38.7	40.4	40.8	50.8	42.0	39.8
PTKP[1]	64.4	82.8	79.8	81.9	45.6	63.4	10.4	25.9	42.5	42.9	48.5	59.4	51.2	49.1
PatchKD[14]	68.5	85.7	75.6	78.6	33.8	50.4	6.5	17.0	34.1	36.8	43.7	53.7	45.1	43.3
KRKC[2]	54.0	77.7	83.4	85.4	48.9	65.5	14.1	33.7	49.9	50.4	50.1	62.5	52.7	50.8
ConRFL[9]	59.2	78.3	82.1	84.3	45.6	61.8	12.6	30.4	51.7	53.8	50.2	61.7	-	-
CODA[50]	53.6	76.9	75.7	78.1	48.6	59.5	13.2	31.3	47.2	48.6	47.7	58.9	44.5	42.4
LSTKC[13]	54.7	76.0	81.1	83.4	49.4	66.2	20.0	43.2	44.7	46.5	50.0	63.1	51.3	48.9
C2R[16]	69.0	86.8	76.7	79.5	33.2	48.6	6.6	17.4	35.6	36.2	44.2	53.7	-	-
DKP[15]	60.3	80.6	83.6	85.4	51.6	68.4	19.7	41.8	43.6	44.2	51.8	64.1	49.9	46.4
Baseline	61.6	79.1	80.2	80.6	50.2	64.3	15.1	36.5	44.9	46.8	50.4	61.5	51.8	49.4
Ours	**75.9**	**87.9**	**87.3**	**88.5**	**60.1**	**71.9**	**25.3**	**50.1**	**60.5**	**61.3**	**61.8**	**71.9**	**60.8**	**58.3**

TABLE II
PERFORMANCE COMPARISON WITH STATE-OF-THE-ART METHODS ON TRAINING ORDER-2. BASELINE MODEL INCLUDES CLIP MODEL AND ATTRIBUTE-TEXT GENERATOR. BOLD AND RED FONTS ARE OPTIMAL AND SUBOPTIMAL VALUES, RESPECTIVELY. TRAINING ORDER-2 IS DUKEMTMC→MSMT17_V2→MARKET→ CUHK-SYSU→ CUHK03.

Method	DukeMTMC		MSMT17_V2		Market1501		CUHK-SYSU		CUHK03		Seen-Avg		Unseen-Avg	
	mAP	R-1	mAP	R-1	mAP	R-1	mAP	R-1	mAP	R-1	mAP	R-1	mAP	R-1
AKA[17]	42.2	60.1	5.4	15.1	37.2	59.8	71.2	73.9	36.9	37.9	38.6	49.4	41.3	39.0
PTKP[1]	54.8	70.2	10.3	23.3	59.4	79.6	80.9	82.8	41.6	42.9	49.4	59.8	50.8	48.2
PatchKD[14]	58.3	74.1	6.4	17.4	43.2	67.4	74.5	76.9	33.7	34.8	43.2	54.1	44.8	43.3
KRKC[2]	50.6	65.6	13.6	27.4	56.2	77.4	83.5	85.9	46.7	46.6	50.1	61.0	52.1	47.7
ConRFL[9]	34.4	51.3	7.6	20.1	61.6	80.4	82.8	85.1	49.0	50.1	47.1	57.4	-	-
CODA[50]	38.7	56.6	11.6	24.5	54.3	75.1	76.2	75.8	42.3	41.7	44.6	54.7	45.0	42.9
LSTKC[13]	49.9	67.6	14.6	34.0	55.1	76.7	82.3	83.8	46.3	48.1	49.6	62.1	51.7	49.5
C2R[16]	59.7	75.0	7.3	19.2	42.4	66.5	76.0	77.8	37.8	39.3	44.7	55.6	-	-
DKP[15]	53.4	70.5	14.5	33.3	60.6	81.0	83.0	84.9	45.0	46.1	51.3	63.2	51.3	47.8
Baseline	53.8	69.1	14.1	29.8	59.8	80.4	78.4	78.5	45.3	44.9	50.3	60.5	52.2	49.9
Ours	**64.1**	**77.2**	**25.4**	**44.9**	**70.6**	**84.5**	**86.1**	**88.2**	**54.2**	**58.7**	**60.1**	**70.7**	**61.6**	**59.2**

E. Attribute-oriented Anti-Forgetting

We develop an attribute-oriented anti-forgetting (AF) strategy to explore attribute-wise representations for aligning the distributions of the old and new models, as shown in Figure 2 (AF). Specifically, the new model adapts to new information but may forget old knowledge from the previous dataset, while the old model retains old knowledge. To better preserve old knowledge, we leverage attribute-wise representations as a bridge to optimize both the old and new models using samples from the memory buffer. This strategy achieves domain consistency and minimize inter-domain gaps, alleviating the forgetting of old knowledge, and is calculated as follows:

$$L_{AF} = \frac{1}{B}\sum_{i=1}^{B} KL(AG_N^{t-1}/\tau || AG_N^{t}/\tau) \tag{8}$$

where $KL(.||.)$ refers to a kullback-leibler divergence, and τ is a hyperparameter called temperature [37].

F. Knowledge Consolidation

Maximizing intra-domain discrimination and minimizing inter-domain gaps are in a contradictory relationship. Therefore, achieving a balance between them is crucial for improving the performance of LReID models. Thus,we propose a knowledge consolidation (KC) strategy that leverages global representations for knowledge transfer between the old and new models. This includes alignment loss and logit-level distillation loss.

Maintaining distribution consistency between the old and new models for previous datasets can limit the model's ability to learn new knowledge. Therefore, we propose an alignment loss to explore global representations for knowledge transfer from the current dataset, as follows:

$$L_{AL} = \frac{1}{B}\sum_{i=1}^{B} KL(G^{t-1}/\tau || G^{t}/\tau) \tag{9}$$

We further introduce a logit-level distillation loss to enhance the extraction of identity information shared between the old and new models, further improving the model's knowledge consolidation ability. This is represented as follows:

$$L_{LD} = \frac{1}{B}\sum_{i=1}^{B} KL((\phi^{t-1}(G^{t-1}))_i/\tau || (\phi^{t}(G^{t}))_i/\tau) \tag{10}$$

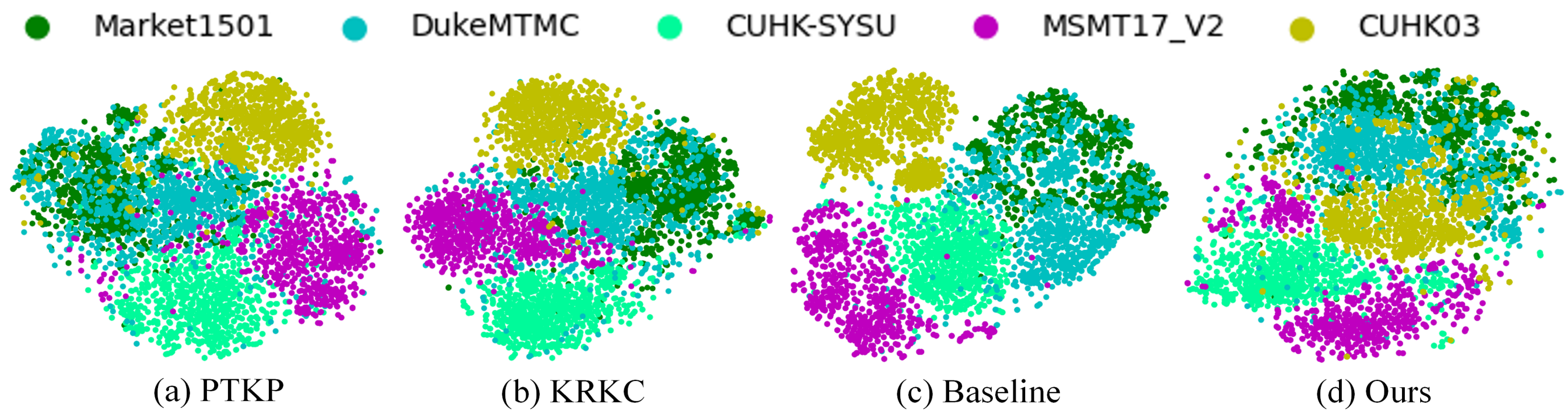

Fig. 3. t-SNE visualization of feature distribution on five seen datasets. Our method better narrows the distribution across datasets for minimizing inter-domain gaps, improving the anti-forgetting and generalization ability of the model.

The knowledge consolidation loss is defined as:

$$L_{KC} = L_{AL} + L_{LD} \tag{11}$$

The total loss function is formulated as:

$$L = L_{CE} + L^{g}_{Tri} + L^{l}_{Tri} + L_{Ort} + L_{AF} + L_{KC} \tag{12}$$

III. Experiments

A. Experiments Setting

Datasets. To verify the performance of our method in anti-forgetting and generalization, we evaluate our method on a challenging benchmark consisting of Market1501 [38], CUHK-SYSU [39], DukeMTMC [40], MSMT17_V2 [41] and CUHK03 [42], referred to as seen datasets. Two representative training orders are set up following the protocol described in [17] for training and testing. Further, we employ six datasets including VIPeR [43], GRID [44], CUHK02 [45], Occ_Duke [46], Occ_REID [47], and PRID2011 [48], as unseen dataset.
Implementation Details. Our text encoder and image encoder are based on a pre-trained CLIP model, while the attribute decoder utilizes a transformer-based architecture[36]. All person images are resized to 256×128. We use Adam [49] for optimization and train each task for 60 epochs. The batch size is set to 128. The learning rate is initialized at 5×10^{-6} and is decreased by a factor of 0.1 every 20 epochs for each task. We employ mean average precision (mAP) and Rank-1 accuracy (R-1) to evaluate the LReID model on each dataset.

B. Comparison with SOTA Methods

We compare the proposed DCR with SOTA LReID to demonstrate the superiority of our method, including AKA[17], PTKP[1], PatchKD[14], KRKC[2], and ConRFL[9], DKP[15], C2R[16], LSTKC[13]. Experimental results on training order-1 and order-2 are shown in Table I and Table II, respectively. CODA [50] method employs ViT-B/16 as the backbone.
Compared with LReID methods. In Table I and Table II, Our DCR significantly outperforms LReID methods, with an seen-avg incremental gain of 10.0% mAP/7.8% R-1, and

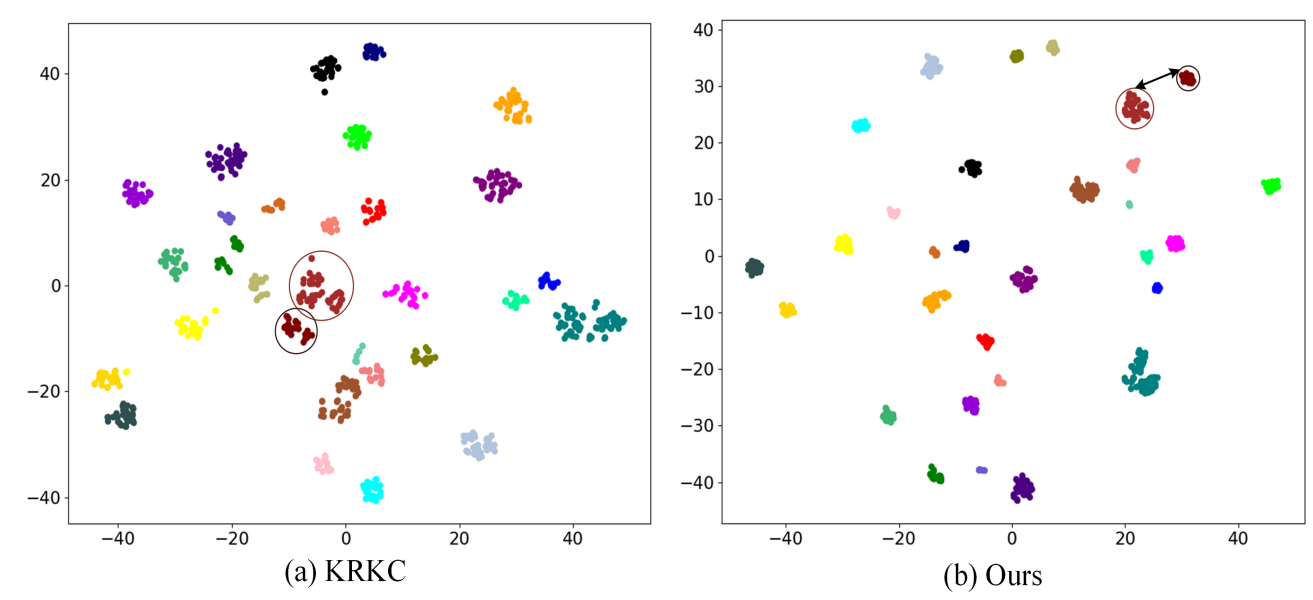

Fig. 4. Visualization of intra-domain discrimination on the Market1501 dataset. We randomly select 30 identities. Colors represent different identity information. Our DCR model can cluster images of the same identity more tightly (circle) for minimizing inter-domian discrimination.

9.8% mAP/7.5% R-1 on training order-1 and order-2, respectively. Meanwhile, our DCR effectively alleviate catastrophic forgetting, achieving 6.9% mAp/1.1% R-1, and 5.4% mAP/ 2.2% R-1 improvement on the first dataset (Mrket1501 and DukeMTMC) with different training orders. Compared to CODA, our DCR significantly outpreform performance under the backbone of VIT-B/16. Additionally, our DCR improves the average by 8.1 mAP%/7.5% R-1 and 9.5% mAP/11.0% R-1 on unseen datasets. In contrast, our DCR achieves a trade-off between anti-forgetting and acquiring new information, significantly enhances generalization capabilities.
Compared with Baseline. Due to the lack of CLIP-based comparison methods in LReID, we introduce a Baseline model including CLIP model, attribute-text generator and knowledge consolidation strategy. Compared to the Baseline, Our DCR improves the Seen-Avg by 11.4% mAP/10.4% R-1 and by 9.8% mAP/10.2% R-1. These results demonstrate that our proposed attribute-wise representations learning achieves significant performance in balancing maximization intra-domain discrimination and minimization inter-domain gaps in LReID.
The effectiveness of minimizing inter-domain gaps. We visualize the feature distribution of PTKP, KRKC, DKP, and our method across five datasets, as shown in Figure 3. DKP shows poor performance in bridging inter-domain gaps, as knowledge prototypes struggle to fit the data distribution. Compared to other methods, our DCR model better narrows the distribution across increasing datasets. Thus, the proposed

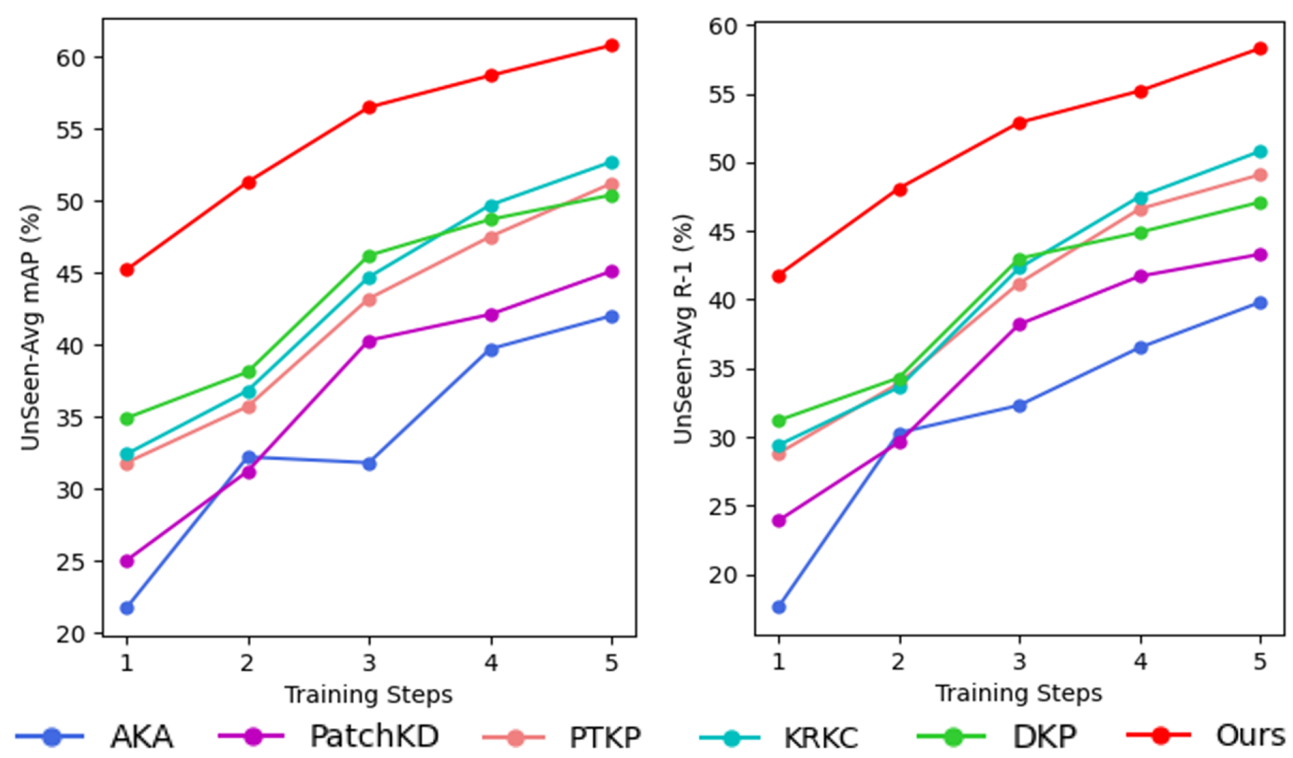

Fig. 5. Generalization curves. After each training step, the performance of all unseen domains is evaluated.

TABLE III
ABLATION STUDIES ON THE NUMBER OF GLOBAL AND ATTRIBUTE-WISE REPRESENTATIONS N ON TRAINING ORDER-1.

Number (N)	Seen_Avg		Unseen_Avg	
	mAP	R-1	mAP	R-1
2	60.2	68.7	59.4	56.5
3	**61.8**	**71.9**	**60.8**	**58.3**
4	61.2	71.6	60.3	57.5

DCR model can effectively bridge domain gaps, improving knowledge transfer capabilities, benefiting from the attribute-oriented anti-forgetting (AF) strategy based on attribute-wise representations.

The effectiveness of maximizing intra-domain discrimination. We visualize the feature distribution of KRKC and our method. Figure 4 shows that our DCR model can significantly cluster images of the same identity more tightly (circle) and increase the distance between different identities (black bidirectional arrow). Compared to KRKC, our DCR model effectively improves intra-domain discrimination, benefiting from the complementary relationship between global and attribute representations, which allows it to learn the subtle nuances of individuals.

Generalization Curves on Unseen Dataset. We analyze the average performance on unseen datasets over the training steps, as shown in Figure 5. Compared to other methods, our DCR model achieves superior performance and exhibits faster performance growth across the training steps. Thus, our attribute-oriented anti-forgetting (AF) strategy effectively bridges inter-domain gaps, enhancing the generalization ability of our model. In summary, our DCR model explores global and attribute-wise representations to achieve a trade-off between maximizing intra-domain discrimination and minimizing inter-domain gaps.

C. Ablation Studies

The number of global and attribute-wise reprentations. Global and attribute-wise representations capture individual nuances in intra-domain and inter-domain consistency. We study the suitability of multiple global and attribute-wise representations, as shown in Table III. We observe that setting the number of global and attribute-wise representations N to 3 achieves the best performance for our method.

TABLE IV
ABLATION STUDIES OF DIFFERENT COMPONENTS ON TRAINING ORDER-1.

PFM	ACN	AF	KC	Seen_Avg		Unseen_Avg	
				mAP	R-1	mAP	R-1
				50.4	61.5	51.8	49.4
√				51.7	62.1	52.5	50.3
√			√	57.6	68.9	58.2	56.2
√	√	√		58.7	69.2	58.5	56.8
√	√	√	√	**61.8**	**71.9**	**60.8**	**58.3**

TABLE V
ABLATION OF TRAINING WITH OR WITHOUT ATTRIBUTE-TEXT GENERATOR (ATG) ON TRAINING ORDER-1.

Method	Seen_Avg		Unseen_Avg	
	mAP	R-1	mAP	R-1
Training w/o ATG	60.1	70.5	59.3	56.5
Training w/ ATG	**61.8**	**71.9**	**60.8**	**58.3**

Performance of Different Components. To assess the contribution of each component to our DCR, we conduct ablation studies on seen and unseen datasets, as shown in Table IV. Comparing the first and second rows, we observe that the parallel fusion module (PFM), which employs a parallel cross-attention mechanism, effectively fuses text and image embeddings. Comparing the second and fourth rows, we consider that the attribute compensation network (ACN) and attribute-oriented anti-forgetting (AF) strategy effectively learn domain consistency, improving generalization ability. In the second and third rows, we notice the performance decrease when using only the knowledge consolidation (KC) strategy based on global representations across increasing data while ignoring inter-domain gaps. The results demonstrate that both global representations and attribute-wise representations achieve a trade-off between maximizing intra-domain discrimination and minimizing inter-domain gaps for enhancing the anti-forgetting and generalization capacity of our DCR.

Performance of attribute-text generator. To better understand whether each instance's text descriptions generated by the attribute-text generator (ATG) provide more fine-grained guidance for learning global representations, we train our model using the generic text descriptor "A photo of a person" (w/o ATG) for comparison. Table V shows that the attribute-text generator obtain text descriptions to significantly improves overall performance. When using the specific text descriptors, the average decreases by 1.7% mAP/1.4% R-1 on seen datasets and by 1.5% mAP/1.8% R-1 on unseen datasets. ATG enhances the robustness of global representations for each instance, effectively mitigating the forgetting of old knowledge.

IV. Conclusion

In this paper, we propose a domain consistency representation learning (DCR) model that explores global and attribute-wise representations to capture subtle nuances in intra-domain and inter-domain consistency, achieving a trade-off between maximizing intra-domain discrimination and minimizing inter-domain gaps. Specifically, global and attribute-wise representations serve as complementary information to distinguish similar identities in intra-domain. We further develop an attribute-oriented anti-forgetting (AF) strategy and a knowledge consolidation (KC) strategy to minimize inter-domain gaps and facilitate knowledge transfer, enhancing generalization capabilities. Extensive experiments demonstrate that our method achieves superior performance compared to state-of-the-art LReID methods.

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