Tackling Domain Shifts in Person Re-Identification: A Survey and Analysis

Vuong D. Nguyen[1], Samiha Mirza[1,*], Abdollah Zakeri[1,*], Ayush Gupta[2,*], Khadija Khaldi[1,*],
Rahma Aloui[1,*], Pranav Mantini[1], Shishir K. Shah[1,†], Fatima Merchant[1]
[1]University of Houston [2]Johns Hopkins University

Abstract

The necessity for a Person ReID system for rapidly evolving urban surveillance applications is severely challenged by domain shifts—variations in data distribution that occur across different environments or times. In this paper, we provide the first empirical review of domain shift in person ReID, which includes three settings namely Unsupervised Domain Adaptation ReID, Domain Generalizable ReID, and Lifelong ReID. We observe that existing approaches only tackle domain shifts caused by cross-dataset setting, while ignoring intra-dataset attribute domain shifts caused by changes in clothing, shape, or gait, which is very common in ReID. Thus, we enhance research directions in this field by redefining domain shift in ReID as the combination of attribute domain shift with cross-dataset domain shift. With a focus on Lifelong Re-ID methods, we conduct an extensive comparison on a fair experimental setup and provide an in-depth analysis of these methods under both non-cloth-changing and cloth-changing Re-ID scenarios. Insights into the strengths and limitations of these methods based on their performance are studied. This paper outlines future research directions and paves the way for the development of more adaptive, resilient, and enduring cross-domain ReID systems. Code is available here.

1. Introduction

Person Re-Identification (ReID) aims to match individuals across non-overlapping camera views, or broadly across distinct observations, as illustrated in Figure 3a. In recent years, ReID has garnered significant attention due to its applications in surveillance, security, human-computer interaction, etc. Traditional ReID benchmarked on standard ReID datasets [17, 28–30, 66, 74, 80–82] using both supervised [4, 31, 59, 77, 84] and unsupervised [6, 24–26, 36, 75] methods have achieved remarkable performance. These methods assume a simplistic single-domain scenario of fixed and stationary data distributions in training process, mostly stemming from observations showing limited geospatial variations and temporal separation between observations. However, the practical deployment of ReID systems is impeded by a fundamental obstacle known as *domain shift*, where *the underlying distributions of data deviates significantly*, leading to a degradation in the model's performance when applied to unseen domains [37]. Though there have been comprehensive reviews on the traditional single-domain ReID setting [41, 72], to the best of our knowledge, **this is the first paper that offers an overview of the real-world problem of domain shift in ReID**.

Conventionally, domain shifts are attributed to cross-dataset changes in observations due to environmental conditions, camera viewpoints, and scene dynamics. This *cross-dataset domain shift* problem has led to three sub-problems in ReID, with an overview shown in Figure 1 and 2. The first sub-problem is to mitigate the domain gaps between a labeled source domain and an unlabeled target domain, which is named Unsupervised Domain Adaptation ReID (UDA-ReID). [34, 79, 87] (see Figure 3b). Three main approaches for UDA-ReID are: (1) Pseudo-label Estimation, which groups similar training samples and assigns pseudo-labels to unlabeled target domain samples, (2) Mid-level

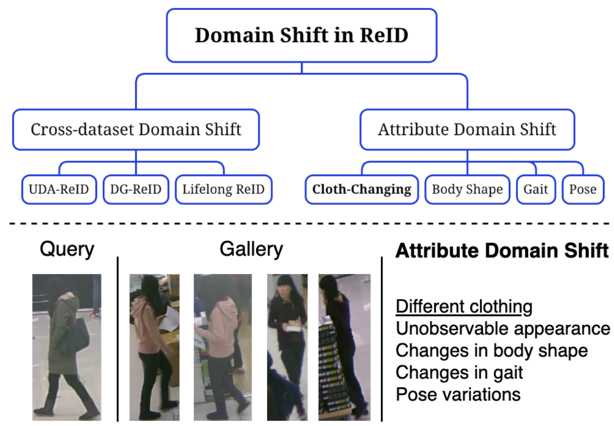

Figure 1. Besides cross-dataset domain shift, attribute domain shift is a common and practical issue in ReID. However, it has not been considered in existing domain-shift-related ReID works.

*: Equal Contribution, †: Corr. author (`sshah@central.uh.edu`)

Feature Alignment, which align feature distributions across different domains, facilitating better generalization, and (3) GAN-based Style Transfer, which use GANs to transfer style from source domain to target domain to bridge the domain gap. UDA-ReID assumes access to the target domain data during training, which does not always hold in real-world scenario. This leads to the more challenging sub-problem named Domain Generalizable ReID (DG-ReID) [7, 57] (see Figure 3c), where the challenge is to learn a model that is robust to unseen target domains given one or multiple labeled source domains. Style Mixing, which simulate domain shifts in DG to learn domain-invariant features, and Meta Learning, which samples domain-level variations and exposes model to cross-domain gaps, are two main approaches for DG-ReID. Both UDA-ReID and DG-ReID assume that all domains are readily available. In specific real-world settings, data can be continuously acquired overtime as a stream of domains. To handle the newly incoming data, practical ReID systems need to address challenges of incremental learning. This sub-problem is current defined as Lifelong ReID (LReID) [19, 50, 68] (see Figure 3d). Two lines of methods that have been proposed for LReID: knowledge distillation-based methods distill knowledge from past models to the current model, and data replay methods store and replay past data samples. Both aim to prevent catastrophic forgetting in LReID. In this paper, we first analyze the solutions proposed to tackle these sub-problems, with a focus on LReID. We also provide insights on advantages and disadvantages of existing LReID methods by providing a fair and comprehensive evaluation on ReID datasets.

Current literature on domain shift has only considered the aforementioned conventional *cross-dataset domain shift* challenges with the strict assumption that individuals within a domain maintain consistent appearances. However, real-world ReID also encounters a common issue of *attribute domain shift*, which encompasses observation variations due to changes in clothing (appearance) [15, 70], body shape [2, 44], gait [16, 32, 45], pose [5, 42], age, etc., as illustrated in Figure 1. Most existing cross-domain methods use deep learning models as backbones, thus they suffer severe performance degradation due to changes in appearance caused by clothing variations. Many recent approaches have been developed to address the specific problem of Cloth-Changing ReID (CCReID) [2, 43, 52]. While this may be viewed as a sub-problem of attribute domain shift, addressing this within the context of cross-dataset domain shift and incremental learning is challenging yet more practical. Thus, in this paper, we introduce a *more practical definition of domain shift in ReID*, which is *the combination of cross-dataset domain shift and attribute domain shift*. Then, the goal is to learn a generalizable model across a stream of data domains while robustly handling large domain shift in individual appearances. To provide insights in the limitations of current cross-domain methods when dealing with attribute domain shift, we conduct a thorough evaluation of existing LReID methods on ReID datasets with and without clothing changes.

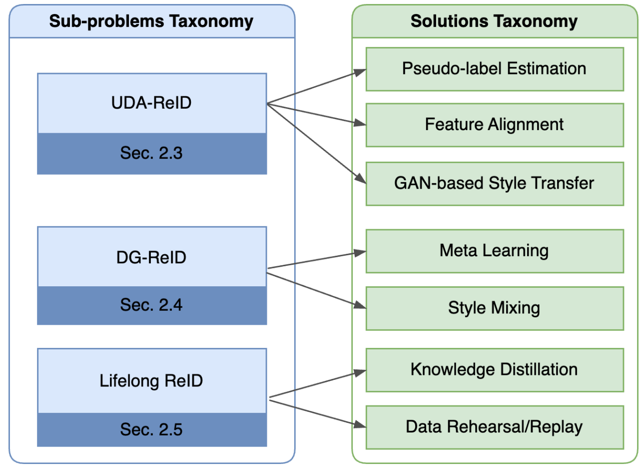

Figure 2. Sub-problems in Domain Shift ReID and Solutions.

The **main contribution** of this paper are as follows:

1. We provide the first review on domain shift in person ReID with a focus on Lifelong ReID.
2. We summarize mainstream solutions that address cross-dataset domain shifts in UDA-ReID, DG-ReID, and LReID. We compare LReID methods using a fair experiment setup, and analyze their strengths and limitations.
3. We introduce the practical issue of attribute domain shift in Re-ID which includes clothing changes, and evaluate existing LReID methods under cloth-changing scenario.
4. We outline promising future research directions.

The remaining of this paper is structured as follows: Section 2 thoroughly reviews solutions associated with cross-domain ReID problems. Section 3 presents experiment setup, while sections 4 and 5 report the evaluation of LReID methods on both standard and cloth-changing ReID setting. Section 6 provides promising research directions and Section 7 presents concluding remarks.

2. Methodologies Review

Person Re-ID task necessitates a model $\mathcal{F}(\cdot)$ such that given a person image I, $\mathcal{F}$ outputs a vector embedding f as the person representation, i.e. $f = \mathcal{F}(I)$. During testing, we compute similarity scores between the query embedding against gallery embeddings. The image with the highest similarity score is considered as the match.

2.1. Unsupervised Domain Adaptation ReID

UDA-ReID aims to adapt a model trained on a labeled source domain to an unlabeled target domain. Three main

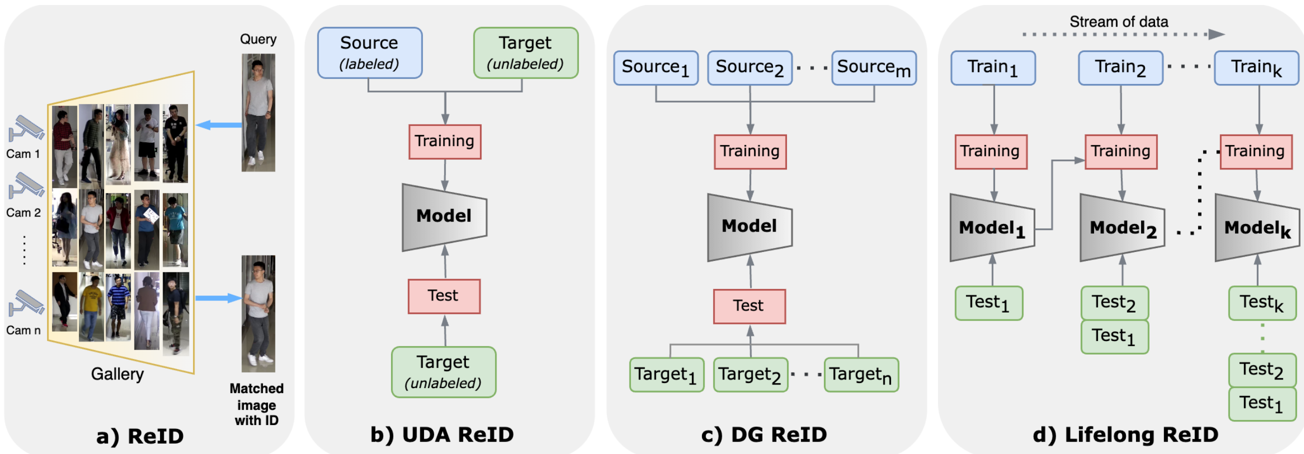

Figure 3. Person ReID task and domain-shift-related ReID settings: UDA-ReID, DG-ReID, and Lifelong ReID.

approaches for UDA-ReID are: Pseudo Label Estimation [54, 55], Mid-Level Feature Alignment [8, 65], and GAN-based Style Transfer [34, 37].

Pseudo Label Estimation. This approach involves using source domain labels to learn initial patterns and apply clustering on the target domain to create pseudo labels for adaptation. Several *labeling-centric* methods [10, 53, 55] have been proposed for enhancing label accuracy and model adaptability. Dynamic Label Update (DLU) [53] exemplifies adaptability by continuously refining pseudo labels to reflect the changing data characteristics of the target domain. Source-Guided Label Refinement (SGLR) [55] leverages knowledge from the source domain to steer the pseudo-labeling process within the target domain, achieving a balance between label accuracy and model stability amid domain shifts. Mutual Mean-Teaching (MMT) [10] leverages a dual-model configuration to mutually refine labels, significantly enhancing label reliability and overall model robustness. *Clustering-based* methods [3, 85–87] involve designing strong identity-related clustering algorithms for pseudo label estimation. Chen *et al*. [3] introduced Hierarchical Contrastive Clustering, utilizing inherent structure from source data to refine pseudo labels. Similarly, Self-paced Refinement and Labeling [85] cycles through data selection and labeling to combat label noise. Zhuang *et al*. [86] normalized feature distribution across cameras, addressing a critical challenge in cross-camera adaptation.

Mid-Level Feature Alignment. Focusing on the alignment of mid-level features, this approach bridges the domain gap by ensuring that features extracted from both domains are comparable and compatible [8, 22, 64, 65]. Wang *et al*. [65] developed a joint learning framework for capturing attribute-semantic and identity-discriminative features, facilitating feature alignment across domains. Fu *et al*. [8] leveraged the underlying pattern within the target domain then employed similarity grouping for effective unsupervised adaptation. Wang *et al*. [64] introduced a memory reconsolidation mechanism to address adversarial domain discrepancies, preserving critical identity information across domains. Huang *et al*. [22] integrates attention mechanisms to selectively emphasize transferable data aspects, effectively reducing the domain gap.

GAN-based Style Transfer. Generative Adversarial Network (GAN) models have been actively explored for bridging the visual gap in UDA-ReID [34, 37, 47, 83]. Early approaches [34, 37] focus on altering the visual style of source domain images to closely match those of the target domain. Liu *et al*. [37] proposed to decompose cross-domain transfer into factor-wise sub-tasks, allowing for precise style adaptation by addressing specific imaging factors like illumination and texture. Li *et al*. [34] presented pose disentanglement and adaptation, achieving pose invariance across domains and significantly enhancing cross-dataset ReID performance. Zheng *et al*. [83] introduced DG-Net, a GAN utilizing dual encoders to extract and transfer appearance attributes from one image to another while preserving the structural integrity of the person. Pang *et al*. [47] proposed TC-GAN, designed to generate labeled images by transferring the person from the input image onto the background of a target style image. Then, the ReID model DFE-Net leverages both real unlabeled and generated labeled images to extract features for ReID.

2.2. Domain Generalizable ReID

DG-ReID involves re-identifying individuals across diverse domains. In this setting, the Re-ID model is trained on a set of source domain(s) and evaluated directly on the target domain(s), without any additional training. Some key strategies to approach DG-ReID include supervised techniques like Meta Learning [12, 57, 76], Style Mixing

[33, 61, 76] and unsupervised/semi-supervised approaches using pseudo labels [7, 51].

Meta Learning. Meta Learning aims to simulate testing stage over multiple training scenarios. During meta-learning stage, rather than sampling instances from each domain, the domains themselves are sampled so the network can learn to generalize to the targets [57]. Focusing on adapting to domain-level variations, Zhang *et al.* [76] sampled domains utilizing curriculum learning to complement meta learning, which adopts an easy-to-hard approach. The idea behind curriculum learning is that like children, the model can learn better when first given easy tasks and gradually increasing the difficulty level of the tasks. For DG-ReID, this involves gradually increasing the number of domains in the training set [11, 76]. Alternatively, models can be trained by initially sampling 'easy' domains and progressively introducing 'hard' domains, offering a graded learning experience [12].

Style Mixing. Rather than using data separately from domains, Style Mixing simulates variations in style, or domain shifts, and use these mixed simulated variations to help the network learn domain-invariant features. Since simulating realistic domain differences in the image space is difficult, most approaches work by tweaking style information in the feature space [33, 61, 76]. Some methods introduce these style features as augmentations [76] into their training pipeline. Others works compute style differences between domains explicitly, and introduce the stylized features in their method by mixing them with the forward pass of the network [33, 61]. For example, Tan *et al.* [61] maintain a 'style memory bank' and keep on updating this memory bank during training. The styles of different domains are 'interleaved' to design new styles within the feature space.

Unsupervised or Semi-Supervised Approaches. Previous approaches necessitate labels from source data, and some even require the incorporation of domain-specific memory banks [46, 61] to effectively handle subjects across different domains. To overcome this limitation, some methods attempt to learn representations in an unsupervised setting to improve scaling in ReID. Generally, the approach involves employing a label-generating network to create pseudo labels for different domains [7, 51]. Qi *et al.* [51] utilize distinct networks for different domains during pseudo-label generation, and train a unified network on all domains using these pseudo labels. On the other hand, Dou *et al.* [7] utilize a quality-aware contrastive loss to assign less weightage to less confident pseudo-labels.

2.3. Lifelong Re-ID

In LReID, after the incremental learning process, model is evaluated on the test data of both seen and unseen domains (see Figure 3d). Thus, it is necessary for the model to both

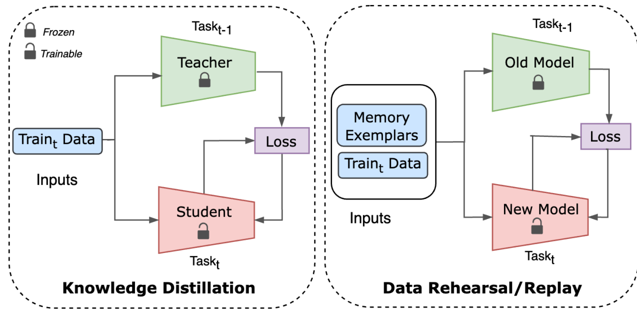

Figure 4. Approaches to prevent catastrophic forgetting in LReID.

memorize the knowledge of seen domains (anti-forgetting) and enhance generalizability on unseen domains. As depicted in Figure 4, two main approaches have been explored for LReID, namely knowledge distillation-based [18, 38, 48–50, 58, 60, 67] and data rehearsal [9, 20, 40, 67, 73] methods. Further, unsupervised LReID has also been investigated [1, 14, 23].

2.3.1 Knowledge Distillation-based Methods

This approach aims to transfer knowledge from past models to the current model via three main strategies: 1) Feature distillation [18, 58, 60, 67], 2) domain-relevant distillation loss [18, 20, 40, 49, 50], and 3) Graph-based Knowledge Distillation [38, 48, 50].

Feature and Logit Distillation. Sugianto *et al.* [58] presented an extension of Learning Without Forgetting (LwF) [35] to the domain of LRe-ID. It evaluated the effectiveness of LwF against other training methods such as fine-tuning and joint-training. It demonstrates the capability of knowledge distillation to preserve identity-related knowledge of previously learned domains. Patch-based Knowledge Distillation (PKD) proposed by Sun *et al.* [60] uses adaptively chosen patches to pilot the forgetting-resistant distillation, guided by logit distillation. Huang *et al.* [18] proposed to learn consistent region features to address catastrophic forgetting and improve generalization. Their method, leveraging property region features, feature adaption, and feature perspicacity, ensures the extraction and distillation of consistent and discriminative features across datasets. A cascade knowledge distillation structure further preserves feature consistency across domains, while a weighted distillation loss minimizes generalization loss.

Knowledge Distillation Losses. Pseudo Task Knowledge Preservation (PTKP) framework developed by Ge *et al.* [9] treats LReID as a domain adaptation problem, utilizing a pseudo task transformation module to bridge the domain gap between consecutive domains and enable the learning of task-shared knowledge. PTKP integrates a domain consistency loss and an identity discrimination loss to pre-

Dataset	Mode	Scale	#TrainIDs	#TestIDs
Market-1501 [81]	Seen	large	500 (751)	750
CUHK-SYSU [69]		mid	500 (942)	2900
DukeMTMC [82]		large	500 (702)	1110
MSMT17 [66]		large	500 (1041)	3060
CUHK03 [30]		mid	500 (767)	700
Viper [13]	Unseen	small	-	316
PRID [17]		small	-	649
GRID [39]		small	-	126
i-LIDS [27]		small	-	60
CUHK01 [29]		small	-	486
CUHK02 [28]		mid	-	239
SenseReID [80]		mid	-	1718
PRCC [71]	CC_{seen}	mid	75 (150)	71
LTCC [52]		mid	75 (77)	75
DeepChange [70]		large	75 (450)	521
Real28 [63]	$\text{CC}_{\text{unseen}}$	small	-	28
VC-Clothes [63]		mid	-	256
Celeb-light [21]		mid	-	200
LaST [56]		large	-	5806

Table 1. Statistics of Standard and Cloth-Changing datasets. The original number of training identities are put inside parentheses.

serve knowledge across tasks, guided by the feature distribution loss on old tasks. Similarly, Pu *et al*. [49] addressed the overlooked issue of mitigating the adverse effects of normalization layers in domain-incremental learning by proposing a novel meta reconciliation normalization (MRN) loss. MRN incorporates grouped mixture standardization and additive rectified rescaling components to balance domain-dependent and domain-independent statistics. Additionally, inspired by synaptic plasticity in the human brain, a MRN-based meta-learning framework is introduced to leverage meta-knowledge across domains without replaying previous data. Lu *et al*. [40] addressed LReID by proposing the Augmented Geometric Distillation loss, which helps maintain feature space structure and preserves relationships between exemplars.

Graph-based Knowledge Distillation. This approach models knowledge via graph and transfers knowledge between steps via graph operations. Adaptive Knowledge Accumulation (AKA) [48] constructs a fully connected graph to retain knowledge during continual learning and is utilized for direct training. Simultaneously, a temporary fully connected graph is constructed using features extracted by the current model. Relevant knowledge is then propagated from the knowledge-preserving graph to the temporary graph using Graph Convolutional Network. Liu *et al*. [38] leveraged the similar idea, but performed knowledge transfer between graphs using Graph Attention Network. Pu *et al*. [50] proposed a graph-based framework built upon AKA, guided by the novel differentiable Ranking Consistency Distillation (RCD). RCD distills ranking knowledge in a differentiable manner, further preventing catastrophic forgetting.

2.3.2 Data Rehearsal/Replay

Inspired by the human brain system, this approach, introduced in Generalising without Forgetting (GwF) by Wu *et al*. [67], stores representative exemplars of old domains, then replays on the current model as knowledge transfer. Yu *et al*. [73] proposed Knowledge Refreshing and Consolidation (KRKC), which incorporates knowledge rehearsal mechanism to enable bi-directional knowledge transfer by introducing a dynamic memory model and an adaptive working model. Huang *et al*. [20] proposed a novel auto-weighted latent embeddings method where autoencoders are used to reconstruct feature maps from both old and new samples at multiple levels. These embeddings are constrained to preserve knowledge from previous tasks, and an adapted auto-weighted approach assigns importance to embeddings based on reconstruction errors.

2.3.3 Unsupervised LReID

To mitigate the requirement for labels in LReID, Chen *et al*. [1] introduced the unsupervised LReID task. This work proposed unsupervised contrastive rehearsal (UCR), which enables a model to adapt to new domains sequentially without supervision. Meanwhile, it preserves knowledge from previous domains by rehearsing a small number of old samples contrastively and applying an image-to-image similarity constraint. UCR regularizes model updates to maintain consistency with old knowledge. LUDA framework introduced by Huang *et al*. [23] enabled deployed models to attain continuous domain adaptation by utilizing unlabeled target streams. LUDA focuses on fine-grained retrieval tasks, necessitating a higher generalizability on unseen identities. Relational Consistency Learning (RCL) assists LUDA in knowledge distillation from historical to current models during adaptation. Gu *et al*. [14] introduced the Color Prompting (CoP) method for data-free continual UDA, leveraging lightweight neural networks to adapt color styles across tasks without storing previous task data, addressing privacy concerns. This approach simulates past domain styles through color distribution fitting and style transfer, significantly enhancing anti-forgetting capabilities and generalization to new domains with minimal labeled data.

3. Experiments Setup

To demonstrate the limitations of existing cross-domain methods in tackling clothing changes, we conduct experiments of existing LReID methods on ReID datasets with and without clothing changes.

ReID without clothing changes. In this setting, we use twelve ReID datasets, which are summarized in Table 1. Following [19, 48, 50, 60], five datasets are used for sequential training (*seen*) with the order *Market-1501*

Method	Venue	Market-1501		CUHK-SYSU		DukeMTMC		MSMT17		CUHK03		Avg. Seen		Avg. Unseen	
		mAP	R-1	mAP	R-1	mAP	R-1	mAP	R-1	mAP	R-1	$\bar{s}_{\text{mAP}}$	$\bar{s}_{\text{R1}}$	$\bar{u}_{\text{mAP}}$	$\bar{u}_{\text{R1}}$
SPD [62]	ICCV'19	35.6	61.2	61.7	63.4	27.6	47.1	5.2	15.5	42.2	44.3	34.4	46.4	40.4	36.6
LwF [35]	TPAMI'17	56.3	77.1	72.9	75.1	29.6	46.5	6.0	16.6	36.1	37.5	40.2	50.6	47.2	42.6
CRL [78]	CVPR'21	58.0	78.2	72.5	75.1	28.3	45.2	6.0	15.8	37.4	39.8	40.5	50.8	47.8	43.5
AKA [48]	CVPR'21	51.2	72.0	47.5	45.1	18.7	33.1	<u>16.4</u>	<u>37.6</u>	27.7	27.6	32.3	43.1	44.3	40.4
AKA† [48]	CVPR'21	58.1	77.4	62.5	64.8	28.7	45.2	6.1	16.2	38.7	40.4	40.8	50.8	47.6	42.6
AGD† [40]	CVPR'22	57.2	80.1	<u>78.0</u>	<u>80.4</u>	35.5	48.2	11.9	20.4	42.8	49.2	<u>45.1</u>	<u>55.7</u>	48.2	43.5
PTKP† [9]	AAAI'22	50.3	74.8	75.4	78.0	<u>41.2</u>	<u>61.5</u>	9.8	26.3	31.7	34.1	41.7	54.9	<u>48.8</u>	<u>44.5</u>
UCR† [1]	arXiv'22	59.3	82.7	78.3	80.0	34.2	46.7	10.1	19.4	40.5	45.9	44.5	54.5	46.4	43.8
PKD [60]	ACMMM'22	**68.5**	**85.7**	75.6	78.6	33.8	50.4	6.5	17.0	34.1	36.8	43.7	53.7	47.1	40.4
PKD† [60]	ACMMM'22	<u>66.1</u>	<u>84.5</u>	73.6	76.2	32.7	48.4	5.8	15.2	32.5	34.6	42.1	51.8	46.3	39.1
KRKC† [73]	AAAI'23	54.6	74.1	73.5	77.3	25.8	40.9	7.2	15.7	35.4	39.2	39.3	49.4	46.0	41.9
RFL [18]	PR'23	59.2	78.3	**82.1**	**84.3**	**45.6**	**61.8**	12.6	30.4	**51.7**	**53.8**	**50.2**	**61.7**	**57.4**	**52.3**
MEGE [50]	TPAMI'23	46.6	67.6	77.2	79.8	21.8	36.1	6.7	18.4	<u>47.8</u>	<u>49.3</u>	40.0	50.2	47.7	44.0
CKP [38]	NN'23	51.2	72.2	73.5	76.8	19.5	33.3	**17.5**	**43.2**	31.4	33.8	38.6	57.9	47.0	40.8

Table 2. Seen-domain Anti-Forgetting evaluation on standard ReID datasets **without clothing changes**. Results are computed after the last training step. "†" means we reproduced results using the released code, while the remaining results are as reported in the literature. Best results are shown in **bold**, while second-to-best results are <u>underlined</u>.

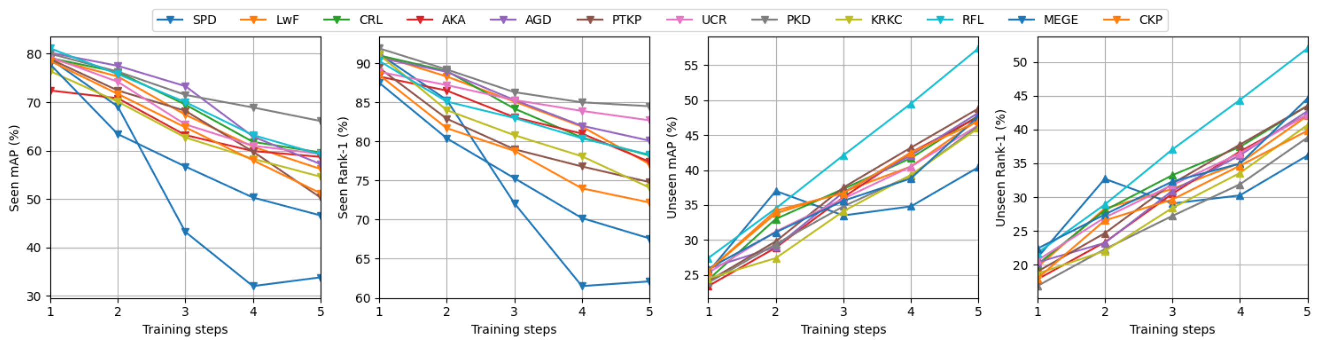

Figure 5. Tendency of (1) anti-forgetting performance on the first seen domain during incremental training process (the first two plots), and (2) generalization performance on unseen domains (the last two plots) on standard ReID datasets **without clothing changes**.

$\rightarrow$ *DukeMTMC-reID* $\rightarrow$ *CUHK-SYSU* $\rightarrow$ *MSMT17* $\rightarrow$ *CUHK03*. This order is applied to all LReID methods for a fair comparison. The remaining eight datasets including Viper, PRID, GRID, i-LIDS, CUHK01, CUHK02, and SenseReID are used as unseen domains to validate the generalizability of LReID methods. Following [48, 60], to mitigate the problem of unbalanced number of identities among datasets, 500 identities are randomly sampled from each seen dataset for training. For testing, the original query and gallery sets are used.

ReID with Clothing Changes. To support the study of LReID under cloth-changing scenario, we propose a benchmark based on existing cloth-changing ReID datasets, named as **LCCReID**, which comprises CC_{seen} and $\text{CC}_{\text{unseen}}$. PRCC, LTCC, and DeepChange datasets are used to construct CC_{seen}. Their training sets are combined for incremental training of LReID methods, while their query and gallery sets are used to evaluate anti-forgetting ability on seen domains. In CC_{seen}, we balance the number of classes among datasets by randomly sampling 75 identities per dataset with a total of 40,152 images. Training order is *PRCC* $\rightarrow$ *LTCC* $\rightarrow$ *DeepChange*. For $\text{CC}_{\text{unseen}}$, we merge the test sets of the remaining four CCReID datasets, Real28, VC-Clothes, Celeb-reID-light, and LaST. This results in a total of 6920 identities and 151,285 images. A summary of LCCReID can be found in Table 1.

Evaluation Metrics. Rank-1 accuracy (R-1) and mean Average Precision (mAP) are computed on each seen domain after each training step. Note that a complete training on one dataset is considered as a training step. Following [50], after the last training step, ($\bar{s}_{R1}$, $\bar{s}_{mAP}$) are computed to measure average anti-forgetting performance on seen domains, while ($\bar{u}_{R1}$, $\bar{u}_{mAP}$) are computed to measure average generalization performance on unseen domains.

Methods and Implementation Details. We conduct evaluation of LReID methods: CRL [78], PTKP† [9], AKA† [48], AGD† [40], UCR† [1], PKD† [60], KRKC† [73], RFL [18], MEGE [50], and CKP [38]. Methods denoted by † provide their open-source code repositories. We also demonstrate the effectiveness of LReID methods compared

Method	Venue	PRCC		LTCC		DeepChange		Avg. Seen		Avg. Unseen	
		mAP	R-1	mAP	R-1	mAP	R-1	$\bar{s}_{\text{mAP}}$	$\bar{s}_{\text{R1}}$	$\bar{u}_{\text{mAP}}$	$\bar{u}_{\text{R1}}$
AKA [48]	CVPR'21	31.2	35.6	10.1	13.4	8.6	31.5	16.6	26.8	14.5	30.1
AGD [40]	CVPR'22	32.0	36.7	10.7	13.9	8.8	32.0	17.2	27.5	<u>16.2</u>	34.5
PTKP [9]	AAAI'22	33.1	37.9	11.8	14.7	<u>9.1</u>	<u>34.9</u>	18.0	29.2	15.8	33.0
UCR [1]	arXiv'22	<u>34.6</u>	<u>38.2</u>	**12.3**	**15.0**	8.9	34.8	<u>18.6</u>	<u>29.3</u>	16.1	<u>34.9</u>
PKD [60]	ACMMM'22	**35.4**	**39.1**	<u>12.0</u>	<u>14.9</u>	**9.3**	**35.3**	**18.9**	**29.8**	**17.8**	**36.2**
KRKC [73]	AAAI'23	33.2	37.4	11.3	13.9	8.9	33.8	17.8	28..4	15.3	33.7

Table 3. Seen-domain Anti-Forgetting evaluation on **CCReID** datasets. We produce results of all six method using their released codes. Best results are shown in **bold**, while second-to-best results are <u>underlined</u>.

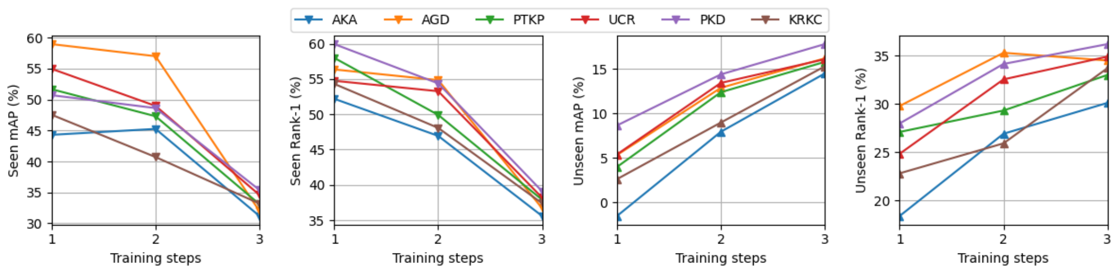

Figure 6. Tendency of (1) anti-forgetting performance on the first seen domain during incremental training process (the first two plots), and (2) generalization performance on unseen domains (the last two plots) on **CCReID**.

to general lifelong learning methods by putting in evaluation: 1) LwF [35] (lifelong learning baseline) and 2) Similarity preserving distillation (SPD) [62]. *On CCReID datasets, no LReID method has been evaluated yet*. Thus, we conduct evaluation among the aforementioned six open-source LReID methods. For fair comparison, we reimplement, train and test these methods using the same experimental setup of 50 training epochs and a batch size of 128. For each batch, 16 identities and 8 images per identity are randomly sampled. Other hyper-parameters are set as reported in the original paper. Experiments were done in PyTorch and conducted on two 32GB Tesla V100 GPUs.

4. Evaluation: ReID without Clothing Changes

We first conduct a comprehensive evaluation of existing LRe-ID methods without clothing changes to provide insights in the strengths and weaknesses of those methods.

Seen Domain Anti-Forgetting Evaluation. We first evaluate the anti-forgetting performance of the reviewed approaches on seen domains, shown in Table 2. Overall, RFL [18] achieves the highest average mAP and R-1 accuracy. It outperforms all other approaches when evaluating on DukeMTMC, CUHK-SYSU, and CUHK03 datasets. RFL uses a cascade knowledge distillation structure to guarantee feature consistency and a weighted distillation loss to prevent generalization loss on current domains caused by overlapping old knowledge, showing effectiveness in mitigating catastrophic forgetting. The second-to-best average performance is achieved by AGD [40], which augments the memory exemplars itself and distillation is conducted in a pair-wise and cross-wise pattern. In Figure 5, we demonstrate forgetting via the decreasing trend of the performance on seen domains during the incremental training process. PKD [60] tends to perform well as training progresses as seen in both mAP and R-1 plots. This is followed by AGD [40] and AKA [48], which also perform well over training steps and this correlates with their distillation ability using memory exemplars.

Unseen Domain Generalization Evaluation. Table 2 presents the average mAP and R-1 score achieved on unseen datasets as generalizability. It can be seen that RFL [18] also outperforms the other methods, achieving an mAP of 57.4% and R-1 score of 52.3%. This is higher than the second-to-best approach PTKP [9] by 8.6% in mAP and by 7.8% in R-1 score. RFL makes use of Feature Perspicacity for diversity feature generation and discriminative feature extraction, which is effective in learning representative ReID features. PTKP [9] uses a mechanism to map new task features onto the feature space of the old tasks and uses task-specific domain consistency loss, which increases its generalizability on unseen domains. AKA [48] and MEGE [50] accumulate knowledge information from old domains via graphs. Figure 5 illustrates the trend of the performance on unseen domains during the incremental training stages. As training progresses, the generalization ability of the approaches improves. Memory exemplar methods [20, 67, 73] tend to perform well on unseen domains due to their ability to adaptively store previous knowledge embeddings and use it to generalize on new tasks.

5. Evaluation: Cloth-Changing ReID

Existing LRe-ID methods ignore attribute domain shifts, particularly clothing changes which is very common in Re-ID. We provide insights into this phenomena via experiments on cloth-changing Re-ID datasets.

Seen Domain Anti-Forgetting Evaluation. On CCReID datasets, comparison in anti-forgetting performance on seen domains is shown in Table 3. Overall, all methods perform much worse than on ReID datasets without cloth-changing, showing the significant influence of clothing changes in Lifelong ReID. PKD [60] achieves the highest average mAP of 18.9% and R-1 accuracy of 29.8%. Its effectiveness in mitigating catastrophic forgetting under cloth-changing scenario lies in its patch-based approach. Local features extracted from patches can contain cloth-invariant features from face or body parts, which is beneficial for LCCReID. The remaining methods that leverage global appearance are severely affected by clothing changes. UCR [1] also shows its ability in preserving knowledge from old domain under cloth-changing scenario, which is lower than PKD by only 0.3/0.5% in average mAP/R-1. This may be reasoned by its unsupervised setting being applied to labeled data. From the visualization of performance tendency as shown in Figure 6, it can be seen that after the second training step on LTCC [52], catastrophic forgetting on PRCC [71] is less severe than after the last training step on DeepChange [70]. This is because compared to DeepChange, LTCC and PRCC present a much smaller range of clothing variations, thus makes it less challenging.

Unseen Domain Generalization Evaluation. The comparison in generalization ability is reported in Table 3 and shown in Figure 6. PKD [60] effectively leverages its patch-based feature extraction to achieve highest generalization performance. AGD [40] achieves second-to-best performance in terms of average mAP. This can be reasoned by its pair-wise and cross-wise feature ranking approach, which helps partially to reduce intra-class gap under clothing changes. However, overall, it is clear that existing LReID methods are not designed for CCReID, shown by low performance results and a small difference in both average mAP and average R-1 accuracy among all methods.

6. Future Directions

Based on the analysis of issues and solutions, the following insights can be drawn for future research to address the Lifelong ReID problem for practical scanarios.

Addressing Attribute Domain Shift. Attributes especially appearance and clothing are likely to change within the same domain. As shown in Tables 2 and 3, existing LReID methods suffer significant performance drop under cloth-changing scenario, which reveals much room for improvement in approaches to solve this problem. Some key strategies can be explored such as: (1) Clothing-guided adaptation techniques that specifically focus on aligning clothing attributes between source and target domains and emphasize the transfer of cloth-irrelevant knowledge while mitigating the influence of other cross-domain factors; (2) Explicitly capturing cloth-invariant cues from body shape or gait, then replaying this knowledge during incremental learning; (3) Leveraging generative models for cloth synthesis or augmentation to mimic the distribution of clothings in target domains.

Improving Generalizability of LReID Methods is another problem to address. As shown in Section 2.3, most existing methods only explicitly tackle catastrophic forgetting issue. Generalization performance of most methods show much room for improvement as shown in Tables 2 and 3.

Efficient Knowledge Preservation and Transfer Methods for LReID that do not require storing and replaying of data should also be developed. This would not only enhance efficiency but also reduces memory for real-world deployment.

Investigation on Different Training Orders of Lifelong ReID is necessary. This includes investigating the impact of adapting to certain domains before others, potentially prioritizing seen domains based on their relevance or similarity to the unseen domain.

Developing Hyperparameter Tuning Strategies tailored for tackling domain shift is also important. This may involve techniques that dynamically adjust hyperparameters based on the characteristics of the current domain.

Exploration of Lifelong ReID in Multimodal Settings is promising. When information from multiple modalities such as visual or text data are available, investigating how Lifelong ReID models can effectively leverage and adapt to diverse modalities to improve ReID performance could enhance robustness for ReID.

7. Concluding Remarks

This paper presents the first review in tackling domain shift in Person ReID. We first explore cross-dataset ReID settings including UDA-ReID and DG-ReID. Then, an in-depth analysis on LReID is conducted. Knowledge Distillation-based and Data Replay methods remain competitive in preserving knowledge and prevent catastrophic forgetting in LReID. However, techniques to enhance generalizability have not been explored. Most importantly, we introduce the novel task of LReID in Cloth-Changing scenario, which encompasses tackling shifts in both data and attributes. Our thorough evaluation of existing LReID methods under both stanard and cloth-changing scenarios provides valuable insights about the strengths and limitations of current approaches. We believe this review and analysis will provide important guidance for future research in domain-shift-related ReID.

References

[1] Hao Chen, Benoit Lagadec, and Francois Bremond. Unsupervised lifelong person re-identification via contrastive rehearsal. *arXiv preprint arXiv:2203.06468*, 2022. 4, 5, 6, 7, 8

[2] Jiaxing Chen, Xinyang Jiang, Fudong Wang, Jun Zhang, Feng Zheng, Xing Sun, and Wei-Shi Zheng. Learning 3d shape feature for texture-insensitive person re-identification. In *CVPR*, pages 8142–8151, 2021. 2

[3] S. Chen, B. Xu, and M. et al. Zhang. Hc-gcn: hierarchical contrastive graph convolutional network for unsupervised domain adaptation on person re-identification. *Multimedia Systems*, 29:2779–2790, 2023. 3

[4] Tianlong Chen, Shaojin Ding, Jingyi Xie, Ye Yuan, Wuyang Chen, Yang Yang, Zhou Ren, and Zhangyang Wang. Abd-net: Attentive but diverse person re-identification. In *ICCV*, pages 8350–8360, 2019. 1

[5] Yeong-Jun Cho and Kuk-Jin Yoon. Pamm: Pose-aware multi-shot matching for improving person re-identification. *IEEE TIP*, 27(8):3739–3752, 2018. 2

[6] Zuozhuo Dai, Guangyuan Wang, Weihao Yuan, Siyu Zhu, and Ping Tan. Cluster contrast for unsupervised person re-identification. In *ACCV*, pages 1142–1160, 2022. 1

[7] Zhaopeng Dou, Zhongdao Wang, Yali Li, and Shengjin Wang. Identity-seeking self-supervised representation learning for generalizable person re-identification. In *ICCV*, pages 15847–15858, 2023. 2, 4

[8] Yang Fu, Yunchao Wei, Guanshuo Wang, Yuqian Zhou, Honghui Shi, and Thomas S Huang. Self-similarity grouping: A simple unsupervised cross domain adaptation approach for person re-identification. In *ICCV*, pages 6112–6121, 2019. 3

[9] Wenhang Ge, Junlong Du, Ancong Wu, Yuqiao Xian, Ke Yan, Feiyue Huang, and Wei-Shi Zheng. Lifelong person re-identification by pseudo task knowledge preservation. In *AAAI*, pages 688–696, 2022. 4, 6, 7

[10] Yixiao Ge, Dapeng Chen, and Hongsheng Li. Mutual mean-teaching: Pseudo label refinery for unsupervised domain adaptation on person re-identification. *arXiv preprint arXiv:2001.01526*, 2020. 3

[11] Tiantian Gong, Kaixiang Chen, Junsheng Wang, and Liyan Zhang. Dynamically Adaptive Instance Normalization and Attention-Aware Incremental Meta-Learning for Generalizable Person Re-identification. In *ICME*, pages 2435–2440, 2023. 4

[12] Tiantian Gong, Kaixiang Chen, Liyan Zhang, and Junsheng Wang. Debiased Contrastive Curriculum Learning for Progressive Generalizable Person Re-Identification. *IEEE TCSVT*, 33(10):5947–5958, 2023. 3, 4

[13] Douglas Gray and Hai Tao. Viewpoint invariant pedestrian recognition with an ensemble of localized features. In *ECCV*, pages 262–275, 2008. 5

[14] Jianyang Gu, Hao Luo, Kai Wang, Wei Jiang, Yang You, and Jian Zhao. Color prompting for data-free continual unsupervised domain adaptive person re-identification. *arXiv preprint arXiv:2308.10716*, 2023. 4, 5

[15] Xinqian Gu, Hong Chang, Bingpeng Ma, Shutao Bai, Shiguang Shan, and Xilin Chen. Clothes-changing person re-identification with rgb modality only. In *CVPR*, pages 1050–1059, 2022. 2

[16] Ayush Gupta and Rama Chellappa. You can run but not hide: Improving gait recognition with intrinsic occlusion type awareness. In *WACV*, pages 5893–5902, 2024. 2

[17] Martin Hirzer, Csaba Beleznai, Peter M Roth, and Horst Bischof. Person re-identification by descriptive and discriminative classification. In *Image Analysis: 17th Scandinavian Conference*, pages 91–102, 2011. 1, 5

[18] Jinze Huang, Xiaohan Yu, Dong An, Yaoguang Wei, Xiao Bai, Jin Zheng, Chen Wang, and Jun Zhou. Learning consistent region features for lifelong person re-identification. *Pattern Recognition*, 144:109837, 2023. 4, 6, 7

[19] Jinze Huang, Xiaohan Yu, Dong An, Yaoguang Wei, Xiao Bai, Jin Zheng, Chen Wang, and Jun Zhou. Learning consistent region features for lifelong person re-identification. *Pattern Recognition*, 144:109837, 2023. 2, 5

[20] Tianjun Huang, Weiwei Qu, and Jianguo Zhang. Continual Representation Learning via Auto-Weighted Latent Embeddings on Person ReID. In *Pattern Recognition and Computer Vision*, pages 593–605, Cham, 2021. 4, 5, 7

[21] Yan Huang, Qiang Wu, Jingsong Xu, and Yi Zhong. Celebrities-reid: A benchmark for clothes variation in long-term person re-identification. In *IJCNN*, pages 1–8, 2019. 5

[22] Y. Huang, P. Peng, Y. Jin, Y. Li, and J. Xing. Domain adaptive attention learning for unsupervised person re-identification. In *AAAI*, pages 11069–11076, 2020. 3

[23] Zhipeng Huang, Zhizheng Zhang, Cuiling Lan, Wenjun Zeng, Peng Chu, Quanzeng You, Jiang Wang, Zicheng Liu, and Zheng-jun Zha. Lifelong unsupervised domain adaptive person re-identification with coordinated anti-forgetting and adaptation. In *CVPR*, pages 14288–14297, 2022. 4, 5

[24] Khadija Khaldi and Shishir K Shah. Cupr: Contrastive unsupervised learning for person re-identification. In *VISIGRAPP (5: VISAPP)*, pages 92–100, 2021. 1

[25] Khadija Khaldi, Pranav Mantini, and Shishir K Shah. Unsupervised person re-identification based on skeleton joints using graph convolutional networks. In *Proceedings of the International Conference on Image Analysis and Processing*, pages 135–146. Springer, 2022.

[26] Khadija Khaldi, Vuong D. Nguyen, Pranav Mantini, and Shishir Shah. Unsupervised person re-identification in aerial imagery. In *WACV Workshops*, pages 260–269, 2024. 1

[27] Ryan Layne, Timothy M Hospedales, Shaogang Gong, and Q Mary. Person re-identification by attributes. In *BMVC*, page 8, 2012. 5

[28] Wei Li and Xiaogang Wang. Locally aligned feature transforms across views. In *CVPR*, pages 3594–3601, 2013. 1, 5

[29] Wei Li, Rui Zhao, and Xiaogang Wang. Human reidentification with transferred metric learning. In *ACCV*, pages 31–44, 2013. 5

[30] Wei Li, Rui Zhao, Tong Xiao, and Xiaogang Wang. Deepreid: Deep filter pairing neural network for person re-identification. In *CVPR*, pages 152–159, 2014. 1, 5

[31] Wei Li, Rui Zhao, Tong Xiao, and Xiaogang Wang. Deepreid: Deep filter pairing neural network for person re-identification. In *CVPR*, pages 152–159, 2014. 1
[32] Weijia Li, Saihui Hou, Chunjie Zhang, Chunshui Cao, Xu Liu, Yongzhen Huang, and Yao Zhao. An in-depth exploration of person re-identification and gait recognition in cloth-changing conditions. In *CVPR*, pages 13824–13833, 2023. 2
[33] Yuke Li, Jingkuan Song, Hao Ni, and Heng Tao Shen. Style-Controllable Generalized Person Re-identification. In *ACM MM*, pages 7912–7921, 2023. 4
[34] Yu-Jhe Li, Ci-Siang Lin, Yan-Bo Lin, and Yu-Chiang Frank Wang. Cross-dataset person re-identification via unsupervised pose disentanglement and adaptation. In *ICCV*, pages 7919–7929, 2019. 1, 3
[35] Zhizhong Li and Derek Hoiem. Learning without forgetting. *IEEE TPAMI*, 40(12):2935–2947, 2017. 4, 6, 7
[36] Yutian Lin, Xuanyi Dong, Liang Zheng, Yan Yan, and Yi Yang. A bottom-up clustering approach to unsupervised person re-identification. In *AAAI*, pages 8738–8745, 2019. 1
[37] Jiawei Liu, Zheng-Jun Zha, Di Chen, Richang Hong, and Meng Wang. Adaptive transfer network for cross-domain person re-identification. In *CVPR*, pages 7195–7204, 2019. 1, 3
[38] Zhaoshuo Liu, Chaolu Feng, Shuaizheng Chen, and Jun Hu. Knowledge-preserving continual person re-identification using graph attention network. *Neural Networks*, 161:105–115, 2023. 4, 5, 6
[39] Chen Change Loy, Tao Xiang, and Shaogang Gong. Time-delayed correlation analysis for multi-camera activity understanding. *IJCV*, 90:106–129, 2010. 5
[40] Yichen Lu, Mei Wang, and Weihong Deng. Augmented geometric distillation for data-free incremental person reid. In *CVPR*, pages 7329–7338, 2022. 4, 5, 6, 7, 8
[41] Zhangqiang Ming, Min Zhu, Xiangkun Wang, Jiamin Zhu, Junlong Cheng, Chengrui Gao, Yong Yang, and Xiaoyong Wei. Deep learning-based person re-identification methods: A survey and outlook of recent works. *Image and Vision Computing*, 119:104394, 2022. 1
[42] Vuong D. Nguyen and Shishir K. Shah. Ccpa: Long-term person re-identification via contrastive clothing and pose augmentation. *arXiv preprint arXiv:2402.14454*, 2024. 2
[43] Vuong D. Nguyen, Khadija Khaldi, Dung Nguyen, Pranav Mantini, and Shishir Shah. Contrastive viewpoint-aware shape learning for long-term person re-identification. In *WACV*, pages 1041–1049, 2024. 2
[44] Vuong D. Nguyen, Pranav Mantini, and Shishir K. Shah. Temporal 3d shape modeling for video-based cloth-changing person re-identification. In *WACV Workshops*, pages 173–182, 2024. 2
[45] Vuong D. Nguyen, Samiha Mirza, Pranav Mantini, and Shishir K. Shah. Attention-based shape and gait representations learning for video-based cloth-changing person re-identification. In *VISIGRAPP (2: VISAPP)*, pages 80–89, 2024. 2
[46] Hao Ni, Yuke Li, Lianli Gao, Heng Tao Shen, and Jingkuan Song. Part-Aware Transformer for Generalizable Person Re-identification. In *ICCV*, pages 11246–11255, 2023. 4
[47] Z. Pang, J. Guo, W. Sun, Y. Xiao, and M. Yu. Cross-domain person re-identification by hybrid supervised and unsupervised learning. *Applied Intelligence*, 2021. 3
[48] Nan Pu, Wei Chen, Yu Liu, Erwin M Bakker, and Michael S Lew. Lifelong person re-identification via adaptive knowledge accumulation. In *CVPR*, pages 7901–7910, 2021. 4, 5, 6, 7
[49] Nan Pu, Yu Liu, Wei Chen, Erwin M. Bakker, and Michael S. Lew. Meta Reconciliation Normalization for Lifelong Person Re-Identification. In *ACM MM*, pages 541–549, New York, NY, USA, 2022. Association for Computing Machinery. 4, 5
[50] Nan Pu, Zhun Zhong, Nicu Sebe, and Michael S Lew. A memorizing and generalizing framework for lifelong person re-identification. *IEEE TPAMI*, 2023. 2, 4, 5, 6, 7
[51] Lei Qi, Jiaqi Liu, Lei Wang, Yinghuan Shi, and Xin Geng. Unsupervised generalizable multi-source person re-identification: A Domain-specific adaptive framework. *Pattern Recognition*, 140:109546, 2023. 4
[52] Xuelin Qian, Wenxuan Wang, Li Zhang, Fangrui Zhu, Yanwei Fu, Tao Xiang, Yu-Gang Jiang, and Xiangyang Xue. Long-term cloth-changing person re-identification. In *ACCV*, pages 71–88, 2021. 2, 5, 8
[53] Hamza Rami, Matthieu Ospici, and Stéphane Lathuilière. Online unsupervised domain adaptation for person re-identification. In *CVPR*, pages 3830–3839, 2022. 3
[54] H. Rami, M. Ospici, and S. Lathuilière. Online unsupervised domain adaptation for person re-identification. In *CVPR*, pages 3830–3839, 2022. 3
[55] Hamza Rami, Jhony H Giraldo, Nicolas Winckler, and Stéphane Lathuilière. Source-guided similarity preservation for online person re-identification. In *WACV*, pages 1711–1720, 2024. 3
[56] Xiujun Shu, Xiao Wang, Xianghao Zang, Shiliang Zhang, Yuanqi Chen, Ge Li, and Qi Tian. Large-scale spatio-temporal person re-identification: Algorithm and benchmark. *IEEE TCSVT*, pages 4390–4403, 2022. 5
[57] Jifei Song, Yongxin Yang, Yi-Zhe Song, Tao Xiang, and Timothy M Hospedales. Generalizable person re-identification by domain-invariant mapping network. In *CVPR*, pages 719–728, 2019. 2, 3, 4
[58] Nehemia Sugianto, Dian Tjondronegoro, Golam Sorwar, Prithwi Chakraborty, and Elizabeth Irenne Yuwono. Continuous Learning without Forgetting for Person Re-Identification. In *IEEE AVSS*, pages 1–8, 2019. 4
[59] Yifan Sun, Liang Zheng, Yi Yang, Qi Tian, and Shengjin Wang. Beyond part models: Person retrieval with refined part pooling (and a strong convolutional baseline). In *ECCV*, page 501–518, 2018. 1
[60] Zhicheng Sun and Yadong Mu. Patch-based knowledge distillation for lifelong person re-identification. In *ACM MM*, pages 696–707, 2022. 4, 5, 6, 7, 8
[61] Wentao Tan, Changxing Ding, Pengfei Wang, Mingming Gong, and Kui Jia. Style Interleaved Learning for Generalizable Person Re-Identification. *IEEE TMM*, 26:1600–1612, 2024. 4
[62] Frederick Tung and Greg Mori. Similarity-preserving knowledge distillation. In *ICCV*, pages 1365–1374, 2019. 6, 7

[63] F. Wan, Y. Wu, X. Qian, Y. Chen, and Y. Fu. When person re-identification meets changing clothes. In *CVPRW*, pages 3620–3628, 2020. 5

[64] G. Wang, J. H. Lai, W. Liang, and G. Wang. Smoothing adversarial domain attack and p-memory reconsolidation for cross-domain person re-identification. In *CVPR*, pages 10565–10574, 2020. 3

[65] J. Wang, X. Zhu, S. Gong, and W. Li. Transferable joint attribute-identity deep learning for unsupervised person re-identification. In *CVPR*, pages 2275–2284, 2018. 3

[66] Longhui Wei, Shiliang Zhang, Wen Gao, and Qi Tian. Person transfer gan to bridge domain gap for person re-identification. In *CVPR*, pages 79–88, 2018. 1, 5

[67] Guile Wu and Shaogang Gong. Generalising without forgetting for lifelong person re-identification. In *AAAI*, pages 2889–2897, 2021. 4, 5, 7

[68] Guile Wu and Shaogang Gong. Generalising without forgetting for lifelong person re-identification. In *AAAI*, pages 2889–2897, 2021. 2

[69] Tong Xiao, Shuang Li, Bochao Wang, Liang Lin, and Xiaogang Wang. Joint detection and identification feature learning for person search. In *CVPR*, pages 3415–3424, 2017. 5

[70] Peng Xu and Xiatian Zhu. Deepchange: A long-term person re-identification benchmark with clothes change. In *ICCV*, pages 11196–11205, 2023. 2, 5, 8

[71] Qize Yang, Ancong Wu, and Wei-Shi Zheng. Person re-identification by contour sketch under moderate clothing change. *IEEE TPAMI*, 43(6):2029–2046, 2021. 5, 8

[72] Mang Ye, Jianbing Shen, Gaojie Lin, Tao Xiang, Ling Shao, and Steven CH Hoi. Deep learning for person re-identification: A survey and outlook. *IEEE TPAMI*, 44(6): 2872–2893, 2021. 1

[73] Chunlin Yu, Ye Shi, Zimo Liu, Shenghua Gao, and Jingya Wang. Lifelong person re-identification via knowledge refreshing and consolidation. In *AAAI*, pages 3295–3303, 2023. 4, 5, 6, 7

[74] Abdollah Zakeri and Hamid Hassanpour. Whispernet: Deep siamese network for emotion and speech tempo invariant visual-only lip-based biometric. In *2021 7th International Conference on Signal Processing and Intelligent Systems (ICSPIS)*, pages 1–5, 2021. 1

[75] Kaiwei Zeng, Munan Ning, Yaohua Wang, and Yang Guo. Hierarchical clustering with hard-batch triplet loss for person re-identification. In *CVPR*, pages 13657–13665, 2020. 1

[76] Lei Zhang, Zhipu Liu, Wensheng Zhang, and David Zhang. Style Uncertainty Based Self-Paced Meta Learning for Generalizable Person Re-Identification. *IEEE TIP*, 32:2107–2119, 2023. 3, 4

[77] Zhizheng Zhang, Cuiling Lan, Wenjun Zeng, Xin Jin, and Zhibo Chen. Relation-aware global attention for person re-identification. In *CVPR*, pages 3183–3192, 2019. 1

[78] Bo Zhao, Shixiang Tang, Dapeng Chen, Hakan Bilen, and Rui Zhao. Continual representation learning for biometric identification. In *CVPR*, pages 1198–1208, 2021. 6

[79] Fang Zhao, Shengcai Liao, Guo-Sen Xie, Jian Zhao, Kaihao Zhang, and Ling Shao. Unsupervised domain adaptation with noise resistible mutual-training for person re-identification. In *ECCV*, pages 526–544, 2020. 1

[80] Haiyu Zhao, Maoqing Tian, Shuyang Sun, Jing Shao, Junjie Yan, Shuai Yi, Xiaogang Wang, and Xiaoou Tang. Spindle net: Person re-identification with human body region guided feature decomposition and fusion. In *CVPR*, pages 1077–1085, 2017. 1, 5

[81] Liang Zheng, Liyue Shen, Lu Tian, Shengjin Wang, Jingdong Wang, and Qi Tian. Scalable person re-identification: A benchmark. In *ICCV*, pages 1116–1124, 2015. 5

[82] Zhedong Zheng, Liang Zheng, and Yi Yang. Unlabeled samples generated by gan improve the person re-identification baseline in vitro. In *CVPR*, pages 3754–3762, 2017. 1, 5

[83] Zhedong Zheng, Xiaodong Yang, Zhiding Yu, Liang Zheng, Yi Yang, and Jan Kautz. Joint discriminative and generative learning for person re-identification. In *CVPR*, pages 2133–2142, 2019. 3

[84] Kaiyang Zhou, Yongxin Yang, Andrea Cavallaro, and Tao Xiang. Omni-scale feature learning for person re-identification. In *ICCV*, pages 3701–3711, 2019. 1

[85] Shuren Zhou, Nanfang Lei, Jiarui Zhou, Jiasi Xiong, and Jianming Zhang. The triple refinement of self-paced learning style for unsupervised cross-domain person re-identification. *Image and Vision Computing*, 141:104870, 2024. 3

[86] Zijie Zhuang, Longhui Wei, Lingxi Xie, Tianyu Zhang, Hengheng Zhang, Haozhe Wu, Haizhou Ai, and Qi Tian. Rethinking the Distribution Gap of Person Re-identification with Camera-Based Batch Normalization. In *ECCV*, pages 140–157, 2020. 3

[87] Yang Zou, Xiaodong Yang, Zhiding Yu, B.V.K. Vijaya Kumar, and Jan Kautz. Joint disentangling and adaptation for cross-domain person re-identification. In *ECCV*, pages 87–104, 2020. 1, 3