Meta Batch-Instance Normalization for Generalizable Person Re-Identification

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Abstract

Although supervised person re-identification (Re-ID) methods have shown impressive performance, they suffer from a poor generalization capability on unseen domains. Therefore, generalizable Re-ID has recently attracted growing attention. Many existing methods have employed an instance normalization technique to reduce style variations, but the loss of discriminative information could not be avoided. In this paper, we propose a novel generalizable Re-ID framework, named Meta Batch-Instance Normalization (MetaBIN). Our main idea is to generalize normalization layers by simulating unsuccessful generalization scenarios beforehand in the meta-learning pipeline. To this end, we combine learnable batch-instance normalization layers with meta-learning and investigate the challenging cases caused by both batch and instance normalization layers. Moreover, we diversify the virtual simulations via our meta-train loss accompanied by a cyclic inner-updating manner to boost generalization capability. After all, the MetaBIN framework prevents our model from overfitting to the given source styles and improves the generalization capability to unseen domains without additional data augmentation or complicated network design. Extensive experimental results show that our model outperforms the state-of-the-art methods on the large-scale domain generalization Re-ID benchmark.

1. Introduction

Person re-identification (Re-ID) aims to identify a specific person across non-overlapping cameras under variant viewpoints and locations. Re-ID has attracted extensive research attention thanks to its practical importance in surveillance systems. With the development of deep Convolutional Neural Networks (CNNs), person Re-ID methods [57, 59, 54, 7, 28] have achieved remarkable performance in a supervised manner, where a model is trained and tested on separated splits of the same dataset. However, this supervised approach is hardly applicable in practice due to expensive labeling costs and also suffers from severe performance degradation on an unseen target domain. To solve this problem, unsupervised domain adaptation (UDA) methods [51, 45, 8, 15, 53, 29] have been introduced to adapt a Re-ID model from a labeled source domain to an unlabeled target domain. The UDA approach is more practical than the supervised approach, but data collection is still required for updating the model on the target domain.

Beyond the concept of UDA, the task of domain generalization (DG) is more plausible for real-world applications since it does not require any target images to train a model. Since Finn et al. [14] propose the Model-Agnostic Meta-Learning (MAML) scheme for few-shot learning and reinforcement learning, several MAML-based methods [3, 22] have been investigated to solve the DG problem. This ap-
proach enables a DG model to achieve a good generalization capability by dividing multiple source domains into meta-train and meta-test domains to mimic real train-test domain shifts. However, most DG methods [3, 22] assume a homogeneous environment, where source and target domains share the same label space, and they are designed for a classification task. In contrast, the task of domain generalization for person re-identification (DG Re-ID) deals with different label spaces between source and target domains for a retrieval task. Thus, it is difficult to obtain good performance when the existing DG methods are directly applied to DG Re-ID.

To this end, the recent DG Re-ID methods [20, 21, 58] pay attention to a combination of batch normalization (BN) [19] and instance normalization (IN) [44]. Jia et al. [20] adopt this idea to Re-ID by inserting IN after the residual connection in the shallow layers, inspired by [35]. However, this approach has a critical issue in that applying IN inevitably causes the loss of discriminative information and also demanding a manual selection of which layer to apply IN. For another instance, Jin et al. [21] design the Style Normalization and Restitution (SNR) module based on instance normalization and feature distillation. Since this method focuses on removing style discrepancy only from the given source domains, it lacks the ability to attenuate the new style of unseen domains sufficiently.

So, how do we design normalization layers to be well generalized for DG Re-ID? To find out the answer, we conducted simple experiments that explore the properties and limitations of BN and IN layers. After training each of the BN and IN models on multiple source domains, we observed the retrieval results on unseen target domains. The BN model strives to learn discriminative information based on the style variations within each mini-batch. However, when samples of unexpected styles are given from unseen target domains, the trained model does not have sufficient ability to distinguish their IDs. We call it under-style-normalization in Fig. 1 (a). On the contrary, IN eliminates instance-specific style information using its own statistics. Even though IN can be helpful to remove unseen styles on target domains, it filters out even some discriminative information, as shown in Fig. 1 (b). We call it over-style-normalization. Since both normalization methods have limitations on the DG setting, the combination of BN and IN has to be handled carefully.

To deal with the above issues, we propose a novel generalizable Re-ID framework, named Meta Batch-Instance Normalization (MetaBIN), for learning to generalize normalization layers. The key idea is to simulate the unsuccessful generalization scenarios mentioned earlier within a meta-learning pipeline and learn more generalized representation from the virtual simulations, as shown in Fig. 1 (c). For this purpose, we design a batch-instance normalization with learnable balancing parameters between BN and IN. Depending on the balancing parameter’s bias toward BN or IN, the DG model suffers from both under-style-normalization and over-style-normalization scenarios in meta-learning. By overcoming these challenging cases, the normalization layer becomes generalized. Moreover, we intentionally diversify the virtual simulations via our meta-train loss and cyclic inner-updating manner to effectively boost the generalization capability. Our MetaBIN framework enables to train the DG model equipped with a sufficient generalization capability to novel domains.

Our main contributions can be summarized as follows:

- We propose a novel generalizable Re-ID framework called MetaBIN. This approach prevents our model from overfitting to the given source styles by generalizing normalization layers via the simulation of unsuccessful generalization scenarios in meta-learning.
- We diversify the virtual simulations through our meta-train loss and a cyclic inner-updating manner. Both ideas effectively boost generalization capability.
- We make comprehensive comparisons and achieve state-of-the-art performance on the large-scale domain generalization Re-ID benchmark.

2. Related Work

**Generalizable person re-identification:** Domain generalizable person re-identification (DG Re-ID) aims to learn a robust model for obtaining good performance on an unseen target domain without additional updates. In recent years, DG Re-ID has attracted a rapidly growing interest owing to its practical applications. Existing methods are categorized into two groups depending on the configuration of source datasets. One is to learn a robust model from a single dataset [58, 21, 26, 41] and the other is to utilize multiple large-scale datasets [40, 43, 20]. Our method belongs to the latter category, which is more useful for real-world applications in that anyone can easily access multiple public Re-ID datasets. In the context of DG Re-ID based on multiple source datasets, Song et al. [40] constructed the large-scale domain generalization Re-ID benchmark to validate the generalization capability of DG models. They also designed Domain-Invariant Mapping Network (DIMN) to learn a mapping between a person image and its ID classifier. However, the additional mapping network slows the inference speed. Tamura et al. [43] suggested a simple selection strategy for data augmentation. While this method is relatively lightweight and easily applicable to other models, it lacks consistency in maintaining generalization capabilities across various unseen styles. For another instance, Jia et al. [20] inserted instance normalization (IN) [44] into each bottleneck in shallow layers to eliminate useless style information, but IN brings about the loss of discriminative
Batch-instance normalization: Normalization techniques are widely used in most of the deep neural network architectures for better optimization and regularization. In particular, a combination of batch normalization (BN) [19] and instance normalization (IN) [44] has recently gained attention as a technique for improving generalization capability to novel domains, which can be divided into non-parametric and parametric methods. The non-parametric methods [20, 35, 58] focus on strategies to replace BN with IN for some layers or add IN to specific locations. However, since their performances depend on where BN and IN are mixed, it is difficult to keep task-independent consistency and requires a lot of trial and error. In contrast, the parametric methods concentrate on how to combine BN and IN in a learnable manner. For example, Nam et al. [34] introduced an effective batch-instance normalization layer through a simple training strategy in which BN and IN are balanced with learnable parameters. Although it has improved recognition performance compared to BN, its learnable manner sometimes leads to overfitting the style of given source domains in the DG setting. In addition, some parametric methods have been studied to handle the following tasks: few-shot learning [4] and homogeneous DG [38]. However, these methods are rarely applicable for DG Re-ID, because evaluation procedures are different from that of DG Re-ID. In this paper, we propose a novel framework that generalizes normalization layers more effectively to solve the challenging DG Re-ID problem.

3. Proposed Method
3.1. Problem Formulation

We begin with a formal description of the domain generalizable person re-identification (DG Re-ID) problem. We assume that we are given \( K \) source domains (datasets) \( \mathcal{D} = \{\mathcal{D}_k\}_{k=1}^{K} \). Each source domain contains its own image-label pairs \( \mathcal{D}_k = \{(x_i^k, y_i^k)\}_{i=1}^{N_k} \), where \( N_k \) is the number of images in the source dataset \( \mathcal{D}_k \). Each sample \( x_i^k \in X_k \) is associated with an identity label \( y_i^k \in Y_k = \{1, 2, \ldots, M_k\} \), where \( M_k \) is the number of identities in the source dataset \( \mathcal{D}_k \). While all domains share the label spaces in the general homogeneous DG setting as \( Y_i = Y_j = Y_* \), \( \forall i, j, 1 \leq i, j \leq K \), source and target domains have completely disjoint label spaces in the DG Re-ID setting as \( Y_i \neq Y_j \). In other words, this task is an application of heterogeneous DG, such that the number of identities in all source domains can be expressed as \( M = \sum_{k=1}^{K} M_k \).

In the training phase, we train a DG model using the aggregated image-label pairs of all source domains. In the testing phase, we perform a retrieval task on unseen target domains without additional model updating.

3.2. Batch-Instance Normalization for DG-ReID

In line with our goal of DG, we employ an instance normalization technique [44] to generalize well on unseen domains. Similar to [34], we design a batch-instance normalizing module as a mixture of BN and IN with learnable balancing parameters for each channel of all normalization layers. Let \( x \in \mathbb{R}^{N \times C \times H \times W} \) be an input mini-batch of a certain layer, where \( N, C, H, \) and \( W \) denote the number of samples in a mini-batch, channels, height, and width, respectively. We combine batch normalization (BN) with instance normalization (IN) as follows:

\[
y = \rho (\gamma_B \cdot \tilde{x}_B + \beta_B) + (1 - \rho) (\gamma_I \cdot \tilde{x}_I + \beta_I),
\]

where the subscripts \( B \) and \( I \) denote variables with respect to BN and IN, \( \tilde{x} \) is the normalized response by mean and variance, \( \gamma, \beta \in \mathbb{R}^C \) are affine transformation parameters, \( \rho \in [0, 1]^C \) is an additional learnable parameter to balance BN and IN. Note that \( \rho \) is a channel-wise parameter for each normalization layer of a feature extractor. Different from [34], we apply each affine transformation to the normalized responses for BN and IN, which allows batch-instance normalization layers to learn various representations.

However, the training mechanism of balancing BN and IN through learnable parameters is a critical issue that can easily overfit the source domain’s styles. In other words, the learnable manner forces the balancing parameters to be optimized depending only on styles existing in source domains. As a result, the normalization layers are unsuccessfully generalized at given unseen target domains, as shown in Fig. 1 (a) and (b). To deal with this problem, we develop our normalization model by using a meta-learning pipeline.
3.3. Meta Batch-Instance Normalization

MetaBIN framework: MLDG [22] is a representative DG method based on Model-Agnostic Meta-Learning (MAML) [14], which enables to train models with a good generalization capability to novel domains through the simulation of real train-test domain-shifts. Inspired by this, we apply the MAML scheme to the updating process of the balancing parameters to prevent our model from overfitting to the source style. To this end, we separate an episode that updates the balancing parameters from another episode that updates the rest of the parameters, and then perform both episodes alternately at each training iteration. The separation of a base model updating process not only ensures baseline performance but also enables effective learning compared to updating all parameters in MLDG [22].

Formally, we denote a classifier \( g_\theta(\cdot) \) parameterized by \( \theta \) and a feature extractor \( f_\phi(\cdot) \) parameterized by \( \phi \), where \( \theta_p \) and \( \phi_f \) are the balancing parameters and the remaining parameters of a feature extractor, respectively. In the base model updating process, we update the parameters of a classifier \( \phi \) and a feature extractor \( \phi_f \) except the balancing parameters \( \theta_p \). In the meta-learning process, only the balancing parameters \( \theta_p \) are updated. The overall methodological flow is summarized in Algorithm 1.

**Base model updates:** In this stage, we update all parameters without the balancing parameters. To this end, we sample a mini-batch \( X_B \) by aggregating the labeled images from all source domains \( D \). We adopt two loss functions for updating a base model. First, we use the cross-entropy loss \( \mathcal{L}_{ce} \) for ID-discriminative learning as follows:

\[
\mathcal{L}_{ce}(X_B; \theta, \phi) = \frac{1}{N_B} \sum_{i=1}^{N_B} \mathcal{L}_{ce}(g_\theta(f_\phi(x_i)), y_i), \tag{2}
\]

where \( N_B \) denotes the number of samples in a mini-batch \( X_B \). In addition, we apply the label smoothing method [42] since there are too many identities in aggregated source domains. It helps to prevent our model from overfitting to training IDs.

Most of the Re-ID methods [11, 48, 21] combine the cross-entropy loss with the triplet loss together for similarity learning. The second loss is expressed as follows:

\[
\mathcal{L}_{tr}(X_B; \theta) = \frac{1}{N_B} \sum_{i=1}^{N_B} \left[ d(f^a_i, f^p_i) - d(f^a_i, f^n_i) + m \right]_+, \tag{3}
\]

where \( f^a_i = f_\phi(x^a_i) \) indicates the feature vector of an anchor sample \( x^a_i \), \( d(\cdot, \cdot) \) is the Euclidean distance, \( m \) is a margin parameter, and \( [z]_+ = \max(z, 0) \). For each sample \( f^a_i \), we select the hardest positive sample \( f^p_i \) and the hardest negative sample \( f^n_i \) within a mini-batch in the same way as [17]. The triplet loss helps to enhance the intra-class compactness and inter-class separability in the Euclidean space. To maximize the synergy between \( \mathcal{L}_{ce} \) and \( \mathcal{L}_{tr} \), we use the BNNeck structure as proposed in [31]. The overall loss is formulated as follows:

\[
\mathcal{L}_{base}(X_B; \theta, \phi) = \mathcal{L}_{ce}(X_B; \theta, \phi) + \mathcal{L}_{tr}(X_B; \theta). \tag{4}
\]

Then we update our base model as follows:

\[
(\theta_f, \phi) \leftarrow (\theta_f - \alpha \nabla_{\theta_f} \mathcal{L}_{base}(X_B; \theta_f, \theta_p, \phi), \phi - \alpha \nabla_{\phi} \mathcal{L}_{base}(X_B; \theta_f, \theta_p, \phi)). \tag{5}
\]

We note that the balancing parameters \( \theta_p \) are not updated.

**Domain-level sampling and meta-learning:** To achieve domain generalization, we split source domains \( D \) into meta-train domains \( D_{mte} \) and meta-test domains \( D_{mte} \) randomly at each iteration. This separation is to mimic real train-test domain-shifts to generalize our normalization layers. In this way, we inner-update the balancing parameters via the meta-train loss, and then validate the updated model at unseen-like meta-test domains. Next, we meta-update the balancing parameters via the meta-test loss. After all, the balancing parameters and base model parameters are alternately generalized in the whole process.

**Meta-train:** Compared to the previous DG methods [22, 3], we introduce a novel concept to significantly improve generalization capability. We start with an explanation of virtual simulations, as shown in Fig. 1 (c). We attempt to simulate unsuccessful generalization scenarios via our meta-train loss by inner-updating the balancing parameters to any space that cannot be explored with the given source domains and general classification loss functions. More specifically, we induce the balancing parameters to be biased toward IN for investigating the virtual over-style-normalization situation where our model becomes much more normalized beyond the styles of the source domain. On the contrary, we also lead to the parameters to be

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**Algorithm 1 MetaBIN**

**Input:** Source domains \( D = \{D_1, D_2, \ldots, D_K\} \), pre-trained parameters \( \theta_f \), hyperparameters \( \alpha, \beta, \gamma \).

**Output:** Feature extractor \( f_\phi(\cdot) \), classifier \( g_\theta(\cdot) \)

1: Initialize parameters \( \theta_p, \phi \\
2: for \text{ ite in iterations do} \\
3: \quad \text{Base model update:} // Eq. (2)-Eq. (5) \\
4: \quad \quad \text{Sample a mini-batch } X_B \text{ from } D. \\
5: \quad \quad \mathcal{L}_{base}(X_B; \theta, \phi) = \mathcal{L}_{ce}(X_B; \theta, \phi) + \mathcal{L}_{tr}(X_B; \theta) \\
6: \quad \quad (\theta_f, \phi) \leftarrow (\theta_f - \alpha \nabla_{\theta_f} \mathcal{L}_{base}(X_B; \theta_f, \theta_p, \phi), \phi - \alpha \nabla_{\phi} \mathcal{L}_{base}(X_B; \theta_f, \theta_p, \phi)) \\
7: \quad \text{Domain-level sampling:} \\
8: \quad \quad \text{Split } D \text{ as } (D_{mtr} \cap D_{mte} = \emptyset, D_{mtr} \cup D_{mte} = D) \\
9: \quad \text{Meta-train:} // Eq. (6)-Eq. (9) \\
10: \quad \quad \text{Sample a mini-batch } X_S \text{ from } D_{mtr}. \\
11: \quad \quad \mathcal{L}_{mte}(X_S; \theta) = \mathcal{L}_{scal}(X_S; \theta) + \mathcal{L}_{mte}(X_S; \theta) + \mathcal{L}_{tn}(X_S; \theta) \\
12: \quad \quad \theta_p \leftarrow \theta_p - \beta \nabla_{\theta_p} \mathcal{L}_{mte}(X_S; \theta_f, \theta_p) \\
13: \quad \text{Meta-test:} // Eq. (10) \\
14: \quad \quad \text{Sample a mini-batch } X_T \text{ from } D_{mte}. \\
15: \quad \quad \theta_p \leftarrow \theta_p - \gamma \nabla_{\theta_p} \mathcal{L}_{tn}(X_T; \theta_f, \theta_p') \\
16: \end{enumerate}
biased toward BN for exploring the virtual under-style-normalization situation in which our model fails to distinguish identities at the unexpected styles. In this way, we design a complementary objective function that can trigger both challenging cases, which provides an opportunity to escape from the local-minima by overcoming the harsh situations at the unseen-like meta-test domain.

To implement this, we first suggest the losses from the perspective of over-style-normalization. Our main point is to enhance intra-domain diversity and disarrange inter-domain distributions like confusing multiple styles. To spread the feature distribution for each domain, we introduce an intra-domain scatter loss as follows:

$$L_{\text{scat}}(X_S; \theta) = \frac{1}{N_S} \sum_{k=1}^{K_S} \sum_{i=1}^{N_S^k} \cos \left( f^k_i, \bar{f}^k \right), \quad (6)$$

where $f^k_i$ denotes the mean feature vector (centroid) of domain $k$ in a mini-batch, $K_S$ is the number of meta-train domains, $N_S^k$ is the number of meta-train samples for domain $k$, $N_S$ is the number of all meta-train samples, and $\cos(a, b) = a \cdot b / \|a\| \|b\|$.

In addition to this, we propose an inter-domain shuffle loss for supporting the virtual effect of style normalization further. This loss pulls the negative sample of the inter-domain and pushes the negative sample of the intra-domain, so that the inter-domains distributions are shuffled. It is expressed as follows:

$$L_{\text{shuf}}(X_S; \theta) = \frac{1}{N_S} \sum_{i=1}^{N_S} l_s \left( d(f^a_i, f^{a-}_i) - d(f^d_i, f^{d+}_i) \right), \quad (7)$$

where $f^a_i$, $f^{a-}_i$, and $f^{d+}_i$ indicate the feature representations of an anchor sample, an inter-domain negative sample, and an intra-domain negative sample. $d(\cdot, \cdot)$ is the Euclidean distance, and $l_s$ is the softplus function [13].

At the same time, we add the triplet loss $L_{\text{tr}}(X_S; \theta)$ from perspective of under-style-normalization. It enhances intra-class compactness regardless style differences. The overall loss for meta-train is as follows:

$$L_{\text{mt}}(X_S; \theta) = L_{\text{scat}}(X_S; \theta) + L_{\text{shuf}}(X_S; \theta) + L_{\text{tr}}(X_S; \theta). \quad (8)$$

The combination of the triplet loss alleviates the excessive discrimination reduction problem caused by $L_{\text{scat}}(X_S; \theta)$ and $L_{\text{shuf}}(X_S; \theta)$.

Based on the meta-train loss $L_{\text{mt}}$, we inner-update the balancing parameters from $\theta_p$ to $\theta^\prime_p$ as follows:

$$\theta^\prime_p = \theta_p - \beta \nabla_{\theta_p} L_{\text{mt}}(X_S; \theta_f, \theta_p), \quad (9)$$

where $\beta$ is a learning rate for the inner-level optimization.

**Cyclic inner-updates:** In the general MAML-based DG methods [22, 3], the learning rate $\beta$ is pre-defined as a constant. To promote the diversity of virtual simulations, we adopt the cyclical learning rate [39] for the inner-level optimization, which we call a cyclical inner-updating method. More specifically, this method affects how much the balancing parameters are updated. Therefore, it diversifies generalization scenarios from the easy case by a small $\beta$ to the difficult case by a large $\beta$.

**Meta-test:** After moving the balancing parameters in the inner-level optimization step, we evaluate our model at the unseen-like samples $X_T$ from meta-test domains $D_{\text{mte}}$. In this step, we can examine various generalization scenarios depending on the movement of the balancing parameters. To validate a retrieval task effectively, we employ the triplet loss with the updated balancing parameters $\theta^\prime_p$ as follows:

$$\theta_p \leftarrow \theta_p - \gamma \nabla_{\theta_p} L_{\text{tr}}(X_T; \theta_f, \theta_p). \quad (10)$$

From the equation, we meta-update the balancing parameters to overcome the virtual simulations. Eventually, our model learns to generalize the balancing parameters by the final optimization process. As these meta-learning and base model updating steps are alternately trained, the generalization capability to unseen domains is improved effectively.

### 4. Experiments

#### 4.1. Datasets and Settings

**Datasets:** To evaluate the generalization capability of the proposed method, we employ the large-scale Re-ID benchmark [40], where the public large-scale Re-ID datasets are combined as multiple source domains and the small-scale Re-ID datasets are used as unseen target domains. Source datasets contain CUHK02 [23], CUHK03 [24], Market-1501 [55], DukeMTMC-ReID [56], and CUHK-SYSU PersonSearch [50], and target datasets include VIPeR [16], PRID [18], GRID [30], and QMUL i-LIDS [49]. All images in the source datasets are used for training regardless of train/test splits, and the total number of identities is $M = 18,530$ with $N = 121,765$ images.

**Implementation details:** Following previous DG Re-ID methods [20, 43, 40], we adopt MobileNetV2 [37] with a multiplier of 1.4 as the backbone network. The weights are pre-trained on ImageNet [12]. Our balancing parameters connect 53 pairs of BN layers and IN layers. The total number of balancing parameters is 23,822, which are initialized to 1. For training, each image is resized to 256 × 128. In a mini-batch, we select 16 samples individually from five source domains. In the base model updating step, all 80 images in one mini-batch are used, whereas in meta-learning, domains are separated into meta-train and meta-test from another mini-batch. The label smoothing parameter is 0.1 and the margin in the triplet loss is 0.3. For updating our base model, we use the SGD optimizer with a momentum of 0.9 and a weight decay of $5 \times 10^{-4}$. Its initial learning rate is 0.01, which is warmed up for 10 epochs as [31] and decayed to its 0.1 × and 0.01 × at 40 and 70 epochs. In the meta-learning step, the balancing parameters are updated by another SGD optimizer without momentum and weight de-
Table 1. Performance (%) comparison with the state-of-the-arts on the large-scale domain generalization Re-ID benchmark, where ‘S’ is supervised learning, ‘UDA’ is unsupervised domain adaptation, ‘DG’ is domain generalization, ‘M’ is Market-1501, ‘MS’ is the multiple source datasets in the DG Re-ID benchmark, ‘Comb1’ is the combination of VIPeR, PRID, CUHK01, i-LIDS, and CAVIAR datasets without each target dataset, and ‘Comb2’ is the combination of CUHK03, DukeMTMC-ReID, and synthetic datasets. 1st and 2nd best results are indicated by red and blue color, respectively.

| Method          | Type | Source | Target: VIPeR (V) [16] | Target: PRID (P) [18] | Target: GRID (G) [30] | Target: i-LIDS (I) [49] |
|-----------------|------|--------|------------------------|-----------------------|------------------------|------------------------|
|                 |      |        | R-1    | R-5    | R-10   | mAP    | R-1    | R-5    | R-10   | mAP    | R-1    | R-5    | R-10   | mAP    |
| DeepRank [5]    | S    | Target | 38.4   | 69.2   | 81.3   | 66.0   | -      | -      | -      | -      | -      | -      | -      | -      |
| NullReID [52]   | S    | Target | 42.3   | 71.5   | 82.9   | 66.0   | -      | -      | -      | -      | -      | -      | -      | -      |
| MTNet [6]       | S    | Target | 47.5   | 73.1   | 82.6   | 62.0   | -      | -      | -      | -      | -      | -      | -      | -      |
| ImpTrpLoss [9]  | S    | Target | 47.8   | 74.7   | 84.8   | 62.0   | -      | -      | -      | -      | -      | -      | -      | -      |
| JLML [25]       | S    | Target | 50.2   | 74.2   | 84.3   | 62.0   | -      | -      | -      | -      | -      | -      | -      | -      |
| SSM [1]         | S    | Target | 53.7   | -      | 91.5   | -      | -      | 37.5   | 61.4   | 69.4   | -      | -      | -      | -      |
| TJ-AIDE [47]    | UDA  | M      | 38.5   | -      | -      | 28.8   | -      | -      | -      | -      | -      | -      | -      | -      |
| MMFA [27]       | UDA  | M      | 39.1   | -      | -      | 28.8   | -      | -      | -      | -      | -      | -      | -      | -      |
| UDML [36]       | UDA  | Comb1  | 31.5   | -      | -      | 24.2   | -      | -      | -      | -      | -      | -      | -      | -      |
| SyRI [2]        | UDA  | Comb2  | 43.0   | -      | -      | 43.0   | -      | -      | -      | 49.3   | -      | -      | -      | -      |
| DIMN [40]       | DG   | M      | 51.2   | 70.2   | 76.0   | 60.1   | 39.2   | 67.0   | 76.7   | 52.0   | 29.3   | 53.3   | 65.8   | 41.1   |
| AugMining [43]  | DG   | MS     | 49.8   | 70.8   | 77.0   | -      | 34.3   | 56.2   | 65.7   | -      | 46.6   | 67.5   | 76.1   | -      |
| DualNorm [20]   | DG   | MS     | 53.9   | 62.5   | 75.3   | 58.0   | 60.4   | 73.6   | 84.8   | 64.9   | 41.4   | 47.4   | 64.7   | 45.7   |
| MetaBin (Ours)  | DG   | MS     | 56.9   | 76.7   | 82.0   | 66.0   | 72.5   | 88.2   | 91.3   | 79.8   | 49.7   | 67.6   | 76.8   | 58.1   

Comparison with unsupervised methods: The UDA method is to leverage large-scale source datasets to improve the performance of a target dataset. In particular, it is different from DG in that unlabeled target samples can be used. We observed that even if unlabeled target samples can be utilized for training, the performance varies significantly according to the composition of training sets. As an example, we have shown that our method can achieve better performance than UDA methods without using any target images.

Comparison with domain generalization methods: Finally, as a fair comparison, we evaluate our MetaBIN framework on the large-scale domain generalization Re-ID benchmark. Among the competitors, DualNorm [20] achieved relatively good performance on VIPeR and PRID, and AugMining [43] also obtained comparable performance on GRID and i-LIDS. Nevertheless, our MetaBIN method clearly outperforms DualNorm [20], AugMining [43], and DIMN [40] by 7.1%, 13.0%, and 17.2% respectively in the average rank-1 accuracy. The main reasons come from two aspects: 1) Our MetaBIN framework, which simulates the virtual scenarios in a meta-learning pipeline, effectively enhances the generalization capability to novel domains; 2) With the addition of simple balancing parameters and the separation of learning episodes, we can solve the challenging heterogeneous DG problem without synthetic data augmentation or complicated network design.

4.3. Ablation study

We perform comprehensive ablation studies to show the effectiveness of our MetaBIN framework and detailed components through the average performance of all datasets.

Influence of model components: Table 2 reports the ablation results of our novel framework including meta-train losses and the cyclic inner-updating method. We employed the cross-entropy and triplet losses as a baseline. We observed that even if unlabeled target samples can be utilized for training, the performance varies significantly according to the composition of training sets. As an example, we have shown that our method can achieve better performance than UDA methods without using any target images.

Evaluation metrics: We follow the common evaluation metrics for Re-ID as mean Average Precision (mAP) and Cumulative Matching Characteristic (CMC) at Rank-κ.

4.2. Comparison with State-of-the-art Methods

The comparison with the state-of-the-art algorithms on VIPeR [16], PRID [18], GRID [30], and i-LIDS [49] are shown in Table 1. The comparison targets are divided into three groups: supervised learning (S), unsupervised domain adaptation (UDA), and domain generalization (DG).

Comparison with supervised methods: Although supervised methods have obtained impressive performance under the large-scale training datasets (e.g. Market-1501 [55] or DukeMTMC-ReID [56]), they suffer from the overfitting issue on the small-scale training datasets. We observed these frustrating results in our experiment. Nonetheless, some of the supervised methods achieved comparable performances on VIPeR. The reason is that the number of its training samples is larger than that of other datasets, which means that expensive labeling costs have to be required inevitably for sustaining high performance. Thus, the supervised approach has the following dilemma: an overfitting problem in a small-scale training set and an impractical problem in a large-scale training set. In contrast, the proposed method is superior to most supervised methods without using labeled target samples.

cay. The meta-train step-size $\beta$ oscillates back and forth in the range $[0.001, 0.1]$ with the triangular policy [39]. The meta-test step-size $\gamma$ is fixed to 0.1. The training stops at 100 epochs, with a total of 1,849 iterations for each epoch. To speed up the training process and increase memory efficiency, we use the automatic mixed-precision training [33] in the entire process and the first-order approximations [14] in meta-optimization. All experiments are conducted on a single NVIDIA Titan Xp GPU using Pytorch.
Table 2. Ablation studies of the proposed MetaBIN framework in the average performance on the DG Re-ID benchmark.

| Method               | $L_{base}$ | $L_{base}^t$ | $\beta$ | R-1 | mAP |
|----------------------|------------|---------------|---------|-----|-----|
| BN                   | -          | -             | fixed   | 50.9 | 59.5 |
| MetaBIN              | $L_{cc}$   | $L_{cc}$      | fixed   | 60.6 | 69.4 |
| MetaBIN              | $L_{cc}, L_{tr}$ | $L_{cc}, L_{tr}$ | fixed   | 62.0 | 69.9 |
| MetaBIN              | $L_{cc}, L_{vat}, L_{shuf}$ | $L_{cc}, L_{tr}$ | fixed   | 63.0 | 71.0 |
| MetaBIN              | $L_{cc}, L_{vat}, L_{shuf}$ | $L_{cc}, L_{tr}$ | cyclic  | 63.5 | 71.3 |
| MetaBIN (replace with BIN [34]) | $L_{cc}, L_{vat}, L_{shuf}$ | $L_{cc}, L_{tr}$ | cyclic  | 64.7 | 72.3 |

Figure 2. Performance (%) and memory usage (MiB) analysis according to the sampling manner of domains and images.

We observed the following aspects: 1) Our novel MetaBIN framework that updates balancing parameters in meta-learning improves the generalization capability with a large performance gap by alleviating the overfitting problem at given source domains; 2) In simulating real train-test domain shifts, the triplet loss is more suitable than the cross-entropy loss for DG Re-ID, which is different from the general homogeneous DG methods [22, 3]; 3) Our meta-train losses are complementary to each other and have a synergistic effect with the cyclic inner-updating method.

**Influence of domain-level sampling:** In this part, we compare the differences depending on the sampling manner of domains and images in the meta-learning step. In Fig. 2 (a), whereas the simulation quality deteriorates if the number of meta-train domains is too small, the generalization capability to overcome the overfitting issues becomes insufficient if the number of meta-test domains is too small. Therefore, the domain sampling between meta-train and meta-test should be adequately balanced. Our method achieved the highest performance and the lowest memory usage when the number of meta-train and meta-test domains were set to be 3 and 2, respectively. Figure 2 (b) shows the performance and memory usage according to the number of images per domain in a mini-batch. It is noteworthy that we chose the highest performance case under the condition that does not exceed the memory usage (7,895MiB) of updating a base model. In other words, the proposed meta-learning pipeline does not increase the memory usage, since the meta-learning and base model updating steps are divided. Thus, it has an advantage in terms of memory consumption over the MLDG method [22] of meta-updating the entire parameters.

Table 3. Performance (%) comparison in a meta-learning pipeline.

| Method               | $L_{base}$ | MLDG [22] | cyclic | R-1 | mAP |
|----------------------|------------|-----------|--------|-----|-----|
| BN                   | $L_{cc}$   | -         | -      | -   | -   |
| MetaBIN (w/o episode separation) | $L_{cc}$, $L_{tr}$ | -         | -      | -   | -   |
| MetaBIN (replace with BIN [34]) | $L_{cc}$, $L_{tr}$ | -         | -      | -   | -   |
| MetaBIN              | $L_{cc}$, $L_{vat}$ | $L_{cc}$, $L_{tr}$ | cyclic | 60.6 | 68.8 |
| MetaBIN (w/o episode separation) | $L_{cc}$, $L_{vat}$ | $L_{cc}$, $L_{tr}$ | cyclic | 60.9 | 69.1 |
| MetaBIN              | $L_{cc}$, $L_{vat}$ | $L_{cc}$, $L_{tr}$ | cyclic | 64.7 | 72.3 |

Table 4. Performance (%) comparison with normalization methods in DG and supervised settings, where ‘S’ is single normalization, ‘N’ is non-parametric normalization, ‘P’ is parametric normalization, ‘BN+IN half’ is a channel-wise combination of BN and IN.

| Method | DG | Supervised (Market1501) |
|--------|----|-------------------------|
| S      | BN | 50.9 | 63.3 | 71.3 | 46.1 |
|       | IN | 54.9 | 63.3 | 71.3 | 46.1 |
| P      | BIN [34] | 54.8 | 63.1 | 79.5 | 53.9 |
|        | MetaBIN (Ours) | 64.7 | 72.3 | 87.5 | 68.5 |

4.4. Further Analysis

**Analysis from the perspective of MAML:** Table 3 presents the experimental results in a meta-learning pipeline. MLDG [22] is a representative MAML-based method designed for homogeneous DG. We observed that MLDG does not improve performance much, which means that it is difficult to directly apply the conventional homogeneous DG method to the challenging DG Re-ID task. On the other hand, when the meta-learning approach is combined with the triplet loss or a batch-instance normalization layer, its performance has been meaningfully improved. Thus, these methods are valid for solving the DG Re-ID problem. However, we note that the generalization potential of the existing BIN model [34] was insufficient compared to our model. The proposed cyclic inner-updating method has made significant improvements in all cases, indicating an effective model-free method. Finally, the separation of training episodes contributed to improving performance considerably. It demonstrates that selectively updating only the balancing parameters in the complicated meta-learning pipeline brings training stability and improves the generalization capacity.

**Analysis from the perspective of normalization:** We analyze our MetaBIN framework and other normalization methods through the performance and t-SNE visualization [32]. First, we compare BN and IN as single normalization techniques. We observed under-style-normalization in Fig. 3 (a) and over-style-normalization in Fig. 3 (b), and it turned out that the performance plummeted when these scenarios occurred as reported in Table 4. Furthermore,
since IN filtered out discriminative information too much, its performance has been greatly degraded in the supervised setting. Meanwhile, the non-parametric or parametric combination of BN and IN alleviated these problems. The non-parametric methods in the DG experiment and the parametric methods in the supervised setting showed relatively high performance. However, a poorly generalized case was also observed at the BIN method [34], as expressed in Fig. 3 (c). On the other hand, our MetaBIN method overcame the overfitting issue by simulating unsuccessful generalization in the meta-learning pipeline, eventually surpassing all normalization methods in the DG experiment. Figure 3 (d) shows that our method has shorter query-gallery distances than those of other methods. Besides, our method improves performance even in the supervised setting. Thus, we demonstrate that our MetaBIN method is generalizable and practical for real-world situations.

Analysis on the balancing parameters: To understand how normalization layers are generalized, we investigate the final distribution ratio of balancing parameters, as shown in Fig. 4. Both experiments were conducted based on MobileNetV2 [37] trained on the large-scale DG Re-ID dataset. Note that all balancing parameters are initialized to 1 (toward BN). We observed that most of the parameters tend to maintain the BN properties, but only some parameters are biased toward IN. Since the performance improved through this process, we demonstrate that removing useless instance-specific style information contributes to improving generalization capability. In particular, the distribution difference between BIN [34] and MetaBIN shows that deflecting some channels toward IN in the middle layer as well as the shallow layer alleviates the overfitting issue and promotes the generalization capability.

Analysis on the meta-train loss: We analyze the virtual simulation scenarios through visualization of gradients calculated in inner-optimization, as illustrated in Fig. 5. First, the intra-domain scatter loss $L_{\text{scat}}$ and inter-domain shuffle loss $L_{\text{shuf}}$ generate positive gradients, which acts to move the balancing parameters in the IN direction. In addition, the triplet loss $L_{\text{tr}}$ promotes negative gradients, which causes the parameters to shift in the BN direction. Eventually, we prove that our meta-train losses induce the balancing parameters in a specific direction, which means that unsuccessful generalization scenarios can be deliberately simulated. We also emphasize that combining all these losses helps improve performance, as shown in Table 2.

5. Conclusion

In this work, we have proposed a novel generalizable person re-identification framework, called Meta Batch-Instance Normalization (MetaBIN). Compared to previous studies, the proposed method alleviates the overfitting problem by investigating unsuccessful generalization scenarios based on our observation. Furthermore, our novel meta-train loss and cyclic inner-updating method diversify virtual simulations and eventually boost generalization capability to unseen domains. Extensive experiments and comprehensive analysis on the large-scale DG benchmark demonstrate its superiority over state-of-the-art methods.
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