Attentive WaveBlock: Complementarity-enhanced Mutual Networks for Unsupervised Domain Adaptation in Person Re-identification

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Abstract

Unsupervised domain adaptation (UDA) for person re-identification is challenging because of the huge gap between the source and target domain. A typical self-training method is to use pseudo-labels generated by clustering algorithms to iteratively optimize the model on the target domain. However, a drawback to this is that noisy pseudo-labels generally cause troubles in learning. To address this problem, a mutual learning method by dual networks has been developed to produce reliable soft labels. However, as the two neural networks gradually converge, their complementarity is weakened and they likely become biased towards the same kind of noise. In this paper, we propose a novel light-weight module, the Attentive WaveBlock (AWB), which can be integrated into the dual networks of mutual learning to enhance the complementarity and further depress noise in the pseudo-labels. Specifically, we first introduce a parameter-free module, the WaveBlock, which creates a difference between two networks by waving blocks of feature maps differently. Then, an attention mechanism is leveraged to enlarge the difference created and discover more complementary features. Furthermore, two kinds of combination strategies, i.e. pre-attention and post-attention, are explored. Experiments demonstrate that the proposed method achieves state-of-the-art performance with significant improvements of 9.4%, 5.9%, 7.4%, and 7.7% in mAP on Duke-to-Market, Market-to-Duke, Duke-to-MSMT, and Market-to-MSMT UDA tasks, respectively.

1 Introduction

The target of person re-identification (re-ID) is to match images of a person across different camera views. Because of its extensive numbers of applications, person re-ID has attracted attention from both academia and industry. In recent years, with the development of deep learning, supervised re-ID methods, such as [26, 28, 23, 4, 20, 46, 42, 2], have gained impressive progress. However, there still exist several drawbacks. First, these methods require intensive manual labeling, which is expensive and time-consuming. Second, due to the domain gap, there is a significant performance drop when a

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model trained on a source domain is tested on a target domain [7,9]. Therefore, unsupervised domain adaptation (UDA) was introduced, which aims at learning a model on a labeled source domain and adapting it to an unlabeled target domain.

Image-level adaptation, such as [7,31], uses a generative adversarial network (GAN) [13] to transfer the image styles of the source domain to a target domain. Feature-level method like [45] investigates underlying feature invariance. However, the performances of these approaches are still unsatisfactory when compared to their fully-supervised counterparts. Recently, several clustering based methods, such as [25,40,10,15], have been proposed, which employ clustering algorithms to group unannotated target images to generate pseudo-labels for training. Although they achieve state-of-the-art performance in various UDA tasks, their abilities are hindered by noisy pseudo-labels caused by the imperfect clustering algorithms and the limited feature transferability.

To address the aforementioned problem, a dual network framework, Mutual Mean-Teaching (MMT) [11] was proposed, which trains two networks simultaneously and utilizes a temporally averaged model to produce reliable soft labels as supervision signals. Although this design reduces the amplification of training error to some degree, as the two networks converge, as shown in Fig. 1, they unavoidably become more and more similar, which weakens their complementarity and may make them bias towards the same kind of noise. This limits further improvement in performance.

To overcome the above limitations, we propose a novel module, namely the Attentive WaveBlock (AWB), under the dual network framework. The critical idea behind AWB is to create a difference between two neural networks to enhance their complementarity. In particular, we first introduce the WaveBlock to modulate feature maps of the two networks with different block-wise waves. Then, we utilize an attention mechanism to force the networks to focus on discriminative features in these regions, which further enlarges the difference between them. Here two kinds of combinations are designed, i.e. pre-attention (Pre-A) and post-attention (Post-A), to produce such different and discriminative features. For Pre-A, the attention modules first learn discriminative features, and then WaveBlocks wave regions differently. For Post-A, WaveBlocks first generate different waves, and then the attention modules learn discriminative features on the different waves. In Fig. 1, we visualize the feature attention maps of the three mutual learning methods using a gradient-weighted class activation map [24] and compute the difference in Frobenius norm between two maps \( A \) and \( B \), which is \( \|A - B\|_F = \sqrt{\sum_{i,j} |a_{ij} - b_{ij}|^2} \). As shown in Fig. 1, from MMT [11] to WaveBlock, the difference increases to some degree. Further, from WaveBlock to AWB, the attention mechanism enlarges the difference created before.

We summarize our contributions as follows:

- We introduce a parameter-free module, the WaveBlock, that can create a difference under the dual network framework. It enhances the complementarity of the two networks and reduces the possibility that they become biased towards the same kind of noise.
- We propose to utilize an attention mechanism to enlarge the difference between networks on the basis of the WaveBlock and design two kinds of combination strategies, i.e. pre-attention and post-attention.
- The AWB module significantly improves performances on UDA tasks for person re-ID, with negligible computational increase. Compared with the state-of-the-art methods, we obtain
improvements of 9.4%, 5.9%, 7.4% and 7.7% in mAP on Duke-to-Market, Market-to-Duke, Duke-to-MSMT, and Market-to-MSMT re-ID tasks.

2 Related Works

2.1 Unsupervised Domain Adaptation for Person Re-ID

Mainstream algorithms for UDA tasks can be categorized into three classes. The first are image-level methods. They use a GAN to transfer the source domain images to the target-domain style [38]. For instance, PTGAN [31] transfers knowledge, while SPGAN [7] focuses on self-similarity and domain-dissimilarity. However, unfortunately, the performance of these methods lags far behind their fully-supervised counterparts. The second category is feature-level methods. For example, [45] investigates three types of underlying invariance, i.e. exemplar-invariance, camera-invariance and neighborhood-invariance. The last category is clustering based adaptation. These methods [9, 19, 40, 10] follow a similar general pipeline: they first pre-train on the source domain and then transfer the learned parameters to fit the target domain. Due to the imperfect clustering algorithms and big domain variance, the generated pseudo labels tend to contain noise, which hinders further improvement in performance. Although, MMT [11] was introduced to alleviate this problem by using a couple of neural networks to generate soft pseudo labels, as the training process goes on, the two neural networks tend to converge and unavoidably share a high similarity. Therefore, it is necessary to consider how to create different networks and enhance the complementarity. This is the starting point of our AWB.

2.2 Attention Mechanism

Attention has been widely used to enhance representation learning in the fields of image classification [27, 21, 36], object detection [3, 39, 8] and so on. For instance, convolutional block attention module (CBAM) [32] uses channel attention and spatial attention to explore "what" and "where" to focus. Non-local block [30] exploits global features. Further, fully-supervised state-of-the-arts person re-ID algorithms, such as ConsAtt [47], SCAL [2], SONA [35], and ABD-Net [4], on several datasets (Market-1501 [41], DukeMTMC [43], CUHK03 [16], MSMT17 [31]) adopt an attention scheme.

2.3 DropBlock

DropBlock was proposed in [12] as a regularization method to drop units in a contiguous region of a feature map. Batch DropBlock Network (BDB) [5] uses a global branch and a feature dropping branch to keep the global salient representations and reinforce the attentive feature learning of local regions. Wu [34] uses multiple dropping branches on the basis of BDB to further boost the performance.

3 Proposed Method

In this section, we first simply review the Mutual Mean-Teaching (MMT) framework, then introduce our WaveBlock module. Finally, we present two different strategies for combining attention mechanism with WaveBlock.

3.1 MMT framework Revisit

Briefly, the MMT framework includes two identical networks with different initializations. Its pipeline is as follows: first, the two networks are pre-trained on the source domain to obtain initialized parameters. Then, in each epoch, offline hard pseudo-labels are generated using a clustering algorithm. In each iteration of a given epoch, refined soft pseudo-labels are produced by the two networks. The hard pseudo-labels and refined soft pseudo-labels generated by one network are then used together to supervise the learning process of the other network. Finally, again in each iteration, the temporally averaged models are updated and used for prediction. For more details, please refer to [11].
Difference

Figure 2: Overview of the WaveBlock module, which creates a difference between two networks by waving blocks of feature maps differently. Specifically, a block is randomly selected and kept the same, while feature values of other blocks are doubled to form a wave.

3.2 WaveBlock

In order to enhance the complementarity of the two networks, we first introduce the WaveBlock module to create a difference between the networks, which is illustrated in Fig. 2. Instead of dropping blocks as in [12] which may lose discriminant information, we modulate a given feature map with different block-wise waves, so that differences are created between dual networks, and meanwhile the original information is preserved to some extent.

Given a feature map $F \in \mathbb{R}^{C \times H \times W}$, where $C$ is the number of channels, $H$ and $W$ are spatial height and width, respectively, and a waving rate $r$, we first generate a random integer with uniform distribution:

$$X \sim U(0, \lfloor H \cdot (1 - r) \rfloor), \quad (1)$$

where $\lfloor \cdot \rfloor$ is the rounding function. Then, we get the WaveBlock modulated feature map as $F^* \in \mathbb{R}^{C \times H \times W}$:

$$F^*_{ijk} =\begin{cases} F_{ijk}, & X \leq j < X + \lfloor H \cdot r \rfloor, \\ 2F_{ijk}, & \text{otherwise}. \end{cases} \quad (2)$$

This design modulates a given feature map with block-wise waves and meanwhile original information is kept to some degree. When applying WaveBlocks to the feature maps $F_1, F_2$ of two networks, respectively, the difference between the networks can be created by waving differently on blocks of feature maps. Let $F^*_1, F^*_2$ denote the output feature maps of WaveBlock and $X_1, X_2$ indicate the waving random integers generated on the two networks; we will calculate the probability that the same wave is generated for both. For simplicity, it is assumed that $F_1$ and $F_2$ have the same size.

In order to enable $F^*_1 = F^*_2$, we should make $X_1 = X_2$. Since

$$P(X_1 = X_2) = \frac{\lfloor H \cdot (1 - r) \rfloor}{[H \cdot (1 - r)]^2} = \frac{1}{[H \cdot (1 - r)]}, \quad (3)$$

we have

$$P(F^*_1 = F^*_2) = P(X_1 = X_2) = \frac{1}{[H \cdot (1 - r)]}. \quad (4)$$

If multiple GPUs are used for training, $X$ will be generated independently in each GPU. In practice, we set $r$ as 0.3 experimentally and four GPUs are used. Then, on feature maps with $H = 16$, we have

$$P(F^*_1 = F^*_2) = \frac{1}{[16 \cdot (1 - 0.3)]^2} = 6.83 \cdot 10^{-5}. \quad (5)$$

Because the probability is too small for the waves of the two networks to be the same, we may say that there is always a difference created between them.

3.3 Attentive WaveBlock

In this section, the attention mechanism is integrated with the WaveBlock module to learn discriminative and different features. Two kinds of combination strategies are designed, including pre-attention (Pre-A) and post-attention (Post-A).

4
3.3.1 Attention Mechanism

To show that the proposed WaveBlock can be combined to general attention methods, two kinds of attention mechanisms are tried here. The first one is the convolutional block attention module (CBAM) [32]. Given a feature map $F \in R^{C \times H \times W}$, CBAM exerts a channel attention map $M_c$ and a spatial attention map $M_s$ on $F$ sequentially:

$$K_1 = M_c (\text{conv}(F)) \otimes \text{conv}(F),$$  \hspace{1cm} (6)

$$K_2 = M_s (K_1) \otimes K_1,$$  \hspace{1cm} (7)

where $\text{conv}$ denotes several convolution blocks and $\otimes$ denotes element-wise multiplication. In CBAM, the channel attention exploits the inter-channel relationship of features, while the spatial attention focuses on “where” an informative part is located.

The second attention mechanism is the Non-local block [30]. Here we adopt its simplified version. Let $F \in R^{C \times H \times W}$ denote a feature map for Non-local block and $\theta$ denote a $1 \times 1$ convolution.

Through $\theta$, the number of channels of $F$ are reduced from $C$ to $C/2$, i.e. $\theta(F) \in R^{C/2 \times H \times W}$. Similarly, another $1 \times 1$ convolution $\phi$ also reduces the number of channels from $C$ to $C/2$, i.e. $\phi(F) \in R^{C/2 \times H \times W}$. Then we collapse the spatial dimension of $\theta(F)$ and $\phi(F)$ into a single dimension, i.e. $\theta'(F) \in R^{C/2 \times HW}$, $\phi'(F) \in R^{C/2 \times HW}$. We obtain our matrix $J \in R^{HW \times HW}$:

$$J = (\theta'(F))^T \cdot \phi'(F).$$  \hspace{1cm} (8)

Next, we adopt $\frac{1}{HW}$ as the scaling factor for $J$, without using $\text{softmax}$. In the other branch, $F$ is fed into a function $g$, which is a $1 \times 1$ convolution followed by a batch normalization layer. Similarly, we collapse the spatial dimension of $g(F)$ into a single dimension and further apply a transpose to get $g'(F) \in R^{HW \times C/2}$. Finally, we multiply $J$ with $g'(F)$, transpose and reshape its dimensions to $C/2 \times H \times W$, and use another $1 \times 1$ convolution $h$ to restore the channel dimension to $C$.

3.3.2 Pre-Attention

As illustrated in Fig. 3(a) to combine the attention module with the WaveBlock, we first try to arrange it before the WaveBlock, which we call the Pre-attention (Pre-A) strategy. In this way, the attention modules first learn discriminative features, and then WaveBlocks wave regions differently to produce different and discriminative features. Given a feature map $F \in R^{C \times H \times W}$, we apply WaveBlock to either of the two attention modules mentioned before and obtain $F' = \text{WaveBlock} (\text{Attention}(F)).$

Here, the attention modules are used to enlarge the difference of the backward gradients generated by the WaveBlock. Although the WaveBlock is able to make the two networks work on different regions of feature maps, some features learned from non-discriminative regions, such as backgrounds, may still be similar. By combining the attention modules with the WaveBlock, the two networks focus on different and discriminative regions, such as the human body, and thus can learn more different features. The advantage of Pre-A is that the attention weights can be computed by using the complete

![Figure 3: Two different combination strategies for the attention module and WaveBlock. WaveBlock creates difference between two networks, while the attention mechanism focuses on learning different and discriminative features.](image-url)
feature maps. This is more beneficial to CBAM because the convolution used to compute its spatial attention will be affected near the border of waved regions.

3.3.3 Post-Attention

The second combination strategy is shown in Fig. 3(b). We arrange the attention mechanism after the WaveBlock, which we call post-attention (Post-A). Correspondingly, the WaveBlocks first wave regions differently, and then the attention modules learn discriminative features on the waved regions to produce different and discriminative features. Given a feature map \( F \in \mathbb{R}^{C \times H \times W} \), after passing through the WaveBlock, either of the two attention modules mentioned before can be applied. This produces \( F^* = \text{Attention}(\text{WaveBlock}(F)) \).

Compared with Pre-A, although the waved regions may affect the computation of the attention weights, directly applying the attention modules on the different waved regions is more efficient for enlarging different features. Post-A is more beneficial to the Non-local block because the non-local operation reduces the impact of waved regions.

4 Experiment

4.1 Datasets and Metrics

Market-1501 [41] was obtained using six different cameras. The dataset has 1,501 labeled persons in 32,668 images. For training, there are 12,936 images of 751 identities. For testing, the query has 3,368 images and gallery has 19,732 images. DukeMTMC-reID [43] contains 1,404 persons from eight cameras. Among them, 16,522 images of 702 identities are used for training. For testing, there are 2,228 queries, and 17,661 gallery images. MSMT17 [31] is the most challenging and largest re-ID dataset. It consists of 126,441 bounding boxes of 4,101 identities taken by 15 cameras. There are 32,621 images for training while the query has 11,659 images and the gallery has 82,161 images. To evaluate our algorithm, we adopt the mean average precision (mAP) and CMC at rank-1, rank-5, and rank-10. No post-processing is used and we utilize single-query evaluation protocols.

4.2 Experimental Settings

We essentially follow the same training settings as MMT [11]. For the source-domain pre-training, to ensure that the improvement comes from a different mutual training but not an enhanced pre-trained network, no change is made, i.e. ResNet-50 [14] is used as the backbone network.

For the first stage of target-domain training, attention modules are trained without WaveBlock engaged. Specifically, for the Non-local block, two attention modules are plugged after Stage 2 and Stage 3 of the ResNet-50 [14] backbone with random initialization. The two modules are trained for 10 epochs with other parameters frozen. For CBAM, we follow the attention mechanism arrangement in [32]. The modules are initialized with ImageNet [6] pre-trained weights. Similarly, they are trained for 40 epochs with other parameters frozen. For the second stage target-domain training, WaveBlock is added into two networks. Specifically, the attention module after Stage 3 of ResNet-50 [14] is integrated with WaveBlock to form AWB. For CBAM, the Pre-A design is used and for Non-local block, the Post-A design is utilized. Because we successfully enhance the complementarity and make it some more difficult for the two neural networks biased towards the same kind of noise, the training process can last for more epochs. We train for 80 epochs with all parameters engaged. When clustering, we select the optimal \( k \) value of \( k \)-means following [11], i.e. 500 for Duke-to-Market, 700 for Market-to-Duke, 1500 for Duke-to-MSMT and Market-to-MSMT. For testing, the WaveBlock is not used.

4.3 Comparison with State-of-the-Arts

To prove the superiority of the AWB under the MMT [11] framework, we compare our model with state-of-the-art methods on four domain adaptations tasks. The comparison results are shown in Table 1. In terms of mAP, we gain a 9.4%, 5.9%, 7.4% and 7.7% improvement on Duke-to-Market, Market-to-Duke, Duke-to-MSMT, and Market-to-MSMT, respectively. As for rank-1, 5.2%, 5.4%, 12.6% and 12.2% improvements are obtained, respectively. Actually, the AWB can improve performance with different \( k \) values stably. For instance, on Duke-to-Market, the Post-A (Non-local) improves
Table 1: Comparison between our method and state-of-the-art algorithms. The results are reported on Market-1501 [41], DukeMTMC [43] and MSMT17 [31].

| Methods          | Duke-to-Market | Market-to-Duke |
|------------------|---------------|---------------|
|                  | mAP | rank-1 | rank-5 | rank-10 | mAP | rank-1 | rank-5 | rank-10 |
| SPGAN [1]        | 22.8 | 51.5 | 70.1 | 76.8 | 22.3 | 41.1 | 56.6 | 63.0 |
| TJ-AIDL [29]     | 26.5 | 58.2 | 74.8 | 81.1 | 23.0 | 44.3 | 59.6 | 65.0 |
| CFSD [11]        | 28.3 | 61.2 | 80.4 | 86.3 | 27.3 | 49.8 | 67.2 | 73.9 |
| UCDA [22]        | 30.9 | 60.4 | 81.2 | 84.7 | 31.0 | 47.7 | 74.5 | 81.2 |
| HHL [44]         | 31.4 | 62.2 | 78.8 | 84.0 | 27.2 | 46.9 | 61.0 | 66.7 |
| BUC [19]         | 38.3 | 66.2 | 79.6 | 84.5 | 27.5 | 47.4 | 62.6 | 68.4 |
| ARN [18]         | 39.4 | 70.3 | 80.4 | 86.3 | 33.4 | 60.2 | 73.9 | 79.5 |
| CDS [33]         | 39.9 | 71.2 | 81.2 | 84.7 | 42.7 | 67.2 | 75.9 | 81.4 |
| ENC [45]         | 43.0 | 75.1 | 87.6 | 91.6 | 40.4 | 63.3 | 75.8 | 80.4 |
| PDA-Net [17]     | 47.6 | 75.2 | 86.3 | 90.2 | 45.1 | 63.2 | 77.0 | 82.5 |
| UDAP [25]        | 53.7 | 75.8 | 89.5 | 93.2 | 49.0 | 68.4 | 80.1 | 83.5 |
| PCB-PAST [40]    | 54.6 | 78.4 | 91.3 | 94.6 | 54.3 | 72.4 | 87.0 | 92.1 |
| SSG [10]         | 58.3 | 80.0 | 90.0 | 92.4 | 53.4 | 73.0 | 80.6 | 83.2 |
| ACT [37]         | 60.6 | 80.5 | 91.3 | 94.6 | 54.5 | 72.4 | 87.0 | 92.1 |
| MMT [11]         | 71.2 | 87.7 | 94.9 | 96.9 | 65.1 | 78.0 | 88.8 | 92.5 |

AWB (Pre-A with CBAM) | 78.0 | 91.5 | 96.5 | 98.1 | 69.1 | 83.3 | 91.3 | 93.8 |
AWB (Post-A with Non-local) | 80.6 | 92.9 | 97.2 | 98.2 | 71.0 | 84.3 | 91.7 | 93.8 |

Table 2: The effectiveness of WaveBlock for creating a difference. "Stage" denotes the position of the WaveBlock. "-s" indicates that the same shape of Waveblock is adopted for both networks.

| Methods          | MMT [11] | Stage 1 | Stage 2 | Stage 3 | Stage 4 | Stage 1-s | Stage 2-s | Stage 3-s | Stage 4-s |
|------------------|----------|--------|--------|--------|--------|----------|----------|----------|----------|
| Duke-to-Market   | mAP | rank-1 | mAP | rank-1 | mAP | rank-1 | mAP | rank-1 | mAP | rank-1 |
|                  | 71.2 | 74.9 | 75.1 | 72.6 | 72.2 | 74.1 | 74.3 | 71.4 |
| Market-to-Duke   | mAP | rank-1 | mAP | rank-1 | mAP | rank-1 | mAP | rank-1 | mAP | rank-1 |
|                  | 65.1 | 70.9 | 79.0 | 80.2 | 81.0 | 79.3 | 79.0 | 79.3 |

mAP from 66.2% to 73.0% and 69.0% to 75.8% when $k$ equals to 700 and 900, respectively; on Market-to-Duke, the Post-A (Non-local) improves mAP from 63.1% to 67.0% and 63.1% to 68.5% when $k$ equals to 500 and 900, respectively.

4.4 Ablation Studies

To prove the efficacy of each component in the AWB, we conduct ablation experiments on DukeMTMC to Market-1501 and Market-1501 to DukeMTMC tasks. The experimental results and analyses are reported below.

Effectiveness of WaveBlock for creating a difference. One WaveBlock is arranged after different stages of ResNet-50 [14], without attention mechanism. As shown in Table 2, arranging WaveBlock in different positions brings various improvements, with Stage 3 being the best position. However, if the same shape of Waveblock is adopted for both networks, performance becomes poorer. Therefore, even without an attention mechanism, the difference created still enhances the complementarity of two neural networks to some degree. In conclusion, it is necessary to introduce the WaveBlock with different shapes to create a difference between two networks.

Effectiveness of the WaveBlock Design. To illustrate the effectiveness of the WaveBlock design, the WaveBlock is replaced with the feature dropping block in [5]. Also, to avoid disturbance, no attention mechanism is used. When the replaced position is scheduled after Stage 4, mAPs are 67.2% and 64.7% for Duke-to-Market and Market-to-Duke tasks, respectively. When the replaced position is scheduled after Stage 3, mAPs are 65.6% and 58.4%, respectively. Compared to using WaveBlock.
Table 3: Comparison between different numbers of WaveBlocks. "Stage" indicates the stages at which the Waveblock is integrated.

| Method    | Duke-to-Market | Market-to-Duke |
|-----------|----------------|----------------|
|           | MMT [11] Stage 2, 3, 4 | Stage 2, 3, 4 |
| mAP       | 71.2           | 65.1           |
| rank-1    | 87.7           | 78.0           |

Table 4: The effectiveness of AWB with CBAM. "CBAM" indicates that only CBAM is used. "Pre-A" denotes the performance of the Pre-A with CBAM while "Post-A" denotes the performance of the Post-A with CBAM.

| Method    | Duke-to-Market | Market-to-Duke |
|-----------|----------------|----------------|
|           | MMT [11] CBAM Pre-A Post-A | MMT [11] CBAM Pre-A Post-A |
| mAP       | 71.2 | 79.0 | 78.0 | 65.1 | 69.6 | 80.6 | 71.0 |
| rank-1    | 87.7 | 90.0 | 91.5 | 89.9 | 78.0 | 80.0 | 83.3 |

as reported in Table[2], the performance of using DropBlock is poorer. The reason is that DropBlock drops some discriminative and important features, which prevents the two neural networks from fitting training data well. In contrast, the proposed Waveblock modulates a given feature map with preserved original feature to some degree.

**How many WaveBlocks are needed in our proposed method?** We try to employ different numbers of WaveBlocks. Experimental results are shown in Table[3]. Compared to Table[2], the conclusion is that it does not gain significant improvement with more WaveBlocks, and using one WaveBlock is enough to create difference between two neural networks.

**Effectiveness of combining the attention mechanism with WaveBlock.** In this part, we try to prove the effectiveness of the attention mechanism in the AWB. Further, two combination designs for two kinds of attention mechanisms are compared. WaveBlock is arranged after Stage 3. The experimental results are displayed in Table[4] and Table[5] respectively. As can be observed, for CBAM, Pre-A combination design is better than CBAM while Post-A combination design is worse than CBAM. It is because the border of the waved feature maps may affect the convolution computing for spatial attention, and the Pre-A design avoids this problem. For Non-local block, the performances of both combination strategies are better than adding Non-local block directly. Specifically, the Post-A design is much better because directly applying attention modules on waved feature maps is more efficient to produce different and discriminative features and non-local operation reduces the impact of waved regions.

**Quantification of the created difference.** The differences created by WaveBlock and enlarged by attention mechanism are quantified in this part. We adopt Post-A with Non-local design, and WaveBlock is arranged after Stage 3. The difference is quantified by calculating the Frobenius norm between two gradient-weighted class activation maps [24] of the same input after Stage 3 or the proposed modules, as illustrated in the introduction section. Further, the differences in Frobenius norm for all images are averaged to obtain final quantified differences. As shown in Table[6] the quantified difference of WaveBlock is larger than MMT’s. The quantified difference is further enlarged by integrating attention mechanism with WaveBlock.

## 5 Conclusion

In this paper, we first propose a parameter-free module, the WaveBlock. Then, we design two kinds of combination methods, i.e. pre-attention and post-attention, to integrate our WaveBlock with the
Table 6: The average differences of two networks in Frobenius norm. "Attention" or "WaveBlock" denotes only attention mechanism or WaveBlock is used. "AWB" denotes the combination of attention mechanism and WaveBlock.

| Method | Duke-to-Market | Market-to-Duke |
|--------|----------------|----------------|
|        | MMT | Attention | WaveBlock | AWB | MMT | Attention | WaveBlock | AWB |
| Difference | 6.84 | 6.97 | 7.43 | 7.89 | 6.72 | 6.70 | 6.90 | 7.80 |

We use the WaveBlock to create a difference between two networks under the framework of MMT. An attention mechanism is also utilized to enlarge the difference and learn different and discriminative features on the basis of WaveBlock. By plugging our AWB into the MMT, the complementarity of the two networks is enhanced and the possibility of their being biased towards the same kind of noise is decreased. Extensive experiments show that our AWB under the MMT framework outperforms the state-of-the-art methods by a large margin.

**Broader Impact**

Unsupervised domain adaptation (UDA) is regarded as an important step to improve person re-identification performance in unknown target domains. That is because, in practical application, it is expensive and time-consuming to label data in an unknown target domain while the transferability of UDA algorithms is able to use unlabeled target data to improve pre-trained models. The practical applications include smart security, intelligent video surveillance and so on. Specifically, it can help us find lost relatives faster and reduce the crime rate in our city. If it is maturely applied, it will liberate a lot of manpower to improve automation and cut costs. However, it may also lead to unemployment of some people, such as security guard.

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