Weak Reverse attention with Context Aware for Person Re-identification

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Abstract. Person re-identification is a difficult topic in computer vision. Some study think that current deep learning methods is biased to capture the most discriminative features and ignore low-level details, more serious is it pay too much attention on relevance between background appearances of person images. It might limit their accuracy or makes them needlessly expensive for a not best performance. In this paper, we carefully design the Weak Reverse attention with Context Aware Network (WRCAnet). Specifically, by merging weak reverse attention network and content aware module, the model can not only remove the background noise to extract the main information of persons, but also suppress the loss of local detailed information as the network deepens. We experiment on the Market-1501, DukeMTMC-reID and CUHK03, and the results show that our method achieves the state-of-the-art performance.

1. Introduction

Person re-ID has received more and more attention from both the scientific and industrial community in recent years due to its wide application prospects. At present, deep learning method has improved the performance of person re-ID to a new level [1-4]. However, some challenges remain.

Firstly, the existing methods almost ignore the impact of the background region on the performance of the person re-ID model. In the field of re-ID, background information has a significant impact on the performance of models[5]. Secondly, in the task of image recognition, more attention is paid to extract the most discriminative features, so with the deepening of network depth, more and more details are ignored.

To solve these problems, we propose Weak Reverse attention with Context Aware network (WRCAnet) for person re-ID. Compared with previous papers, there are the following three contributions in this paper:

- We propose a weak anti-attention mechanism to eliminate background-bias for Robust Person Re-identification. It should be the first time that weak reverse attention has been proposed.
- We designed a content perception module based on multi-stage feature fusion and multi-granularity feature fusion, which can extract multi-scale and more refined features.
- The experimental results show that the proposed method achieves state-of-the-art performance.
on the three benchmarks of Market-1501, DukeMTMC-reID and CHUK03.

2. Related Work
In recent years, attention mechanisms have been widely used in re-ID [6-8]. [6] uses a combination of spatial attention and channel attention to extract global features, and uses channel attention to extract local features. Li et al. [7] adds a multi-branch harmonious attention mechanism to Resnet to reduce the number of parameters and extract multi-local features. In addition, attention mechanism based on attribute guidance and attitude estimation has been widely used. Xu J et al. [8] utilized pose-guided part Attention to locate body part so that can Extract pedestrian features to re-ID.

It has been proved that using multi-level method is a powerful technique for learning high-level semantic features and solving the issue of misalignment of body parts [9-12]. In this paper, a content aware module is designed, which is composed of multi-scale feature fusion and multi-granularity feature fusion to integrate more useful information to prevent information loss with the deepening of the network.

3. Proposed Method
3.1. Overall Architecture
In this paper, shown in Figure 1, we build the model based ResNet-50. In order to obtain larger feature map and more information, we modified the stride of last down-sampling operation from 2 to 1, do as the successful methods [1] do.

According to [13], the Resnet consists of 4 residual modules. The output features are also different at different stages. In the lower stage, feature maps often have good spatial position expression capabilities. While in the high stage, they have strong contextual ability and more semantic information. However, no matter in what stage, it extracts the global information of the image, which has the ability to express the global information. Multi-level fusion can complement the defects of deep features and shallow features. Therefore, we design a channel attention method similar to Senet [14] to fuse features as an expression of multi-scale information.
3.2. Backbone Network with Weak Reverse Attention
We propose a model Resnet + weak reverse attention model different from the existing methods[8], as shown in Figure 2.

\[ \alpha_c = \frac{1}{H \times W} \sum_i \sum_j A_{ij} \]  

in order to get the attention map, the channel needs to be reduced to a single channel, so the weighted average operation is done along the channel. We define the upsampling operation \( \text{upsample}(\cdot) \) to align the size of the feature map with the input. After the activation function \( \text{relu} \), the most discriminative feature map \( f_{ij} \) described above is defined as formula (2):

\[ f_{ij} = \text{ReLU}(\text{upsample}(\frac{1}{C} \sum \alpha_c \otimes A_{ij})) \]  

The input feature minus this most discriminative feature map, which is the same size as the input feature, is the reverse attention described in [1]. We define weak reverse attention as formula (3). The parameter \( \alpha \in (0,1) \) is the weakening coefficient, which is 0.5 in this paper.

\[ f_{\text{new}} = I \otimes (1 - \alpha \cdot \text{sigmoid}(f_{ij})) \]  

3.3. Context Aware
Content perception in this paper is composed of multi-scale fusion module and multi-granularity fusion module.

Multi-scale Feature fusion. In different stages, the residual module outputs different sizes of feature maps. This paper compressed the output feature of the four modules of Resnet to the same size.
(24*12) through the AdaptiveAvgPool operation. Then, the weight of each group of features is obtained through global pooling, and a 1-dimensional convolution is used to fuse the four feature graphs to get a 1*288-dimensional fusion feature, as shown in figure 3.

**Multi-granularity Feature fusion.** In order to obtain the multi-granularity features of the image, we designed a GP branch network, as shown in Figure 4. The global maximum pooling (GMP) feature and global minimum pooling (GAP) feature are taken for the output of each level of residual module, then the sum of the pooling features is calculated, and then a convolution layer whose kernel size and stride is 1 is connected to reduce the channels to 256. Figure 5 shows the structure of a multi-granularity feature fusion network. Similar to multi-scale feature fusion, we connect four 1*256 features and then use a one-dimensional convolution to fuse to a 1*256-dimensional multi-granularity feature.

**Figure 3.** Multi-scale Feature fusion. The channel attention is achieved by global pooling and one-dimensional convolution.

**Figure 4.** GP net. It is composed of maximum pooling, average pooling and convolution with kernel=1.

**Figure 5.** Multi-granularity Feature fusion. The input features are connected, and convolution is used to fuse these features.

### 3.4. Loss function

In the network, we use the sum of loss functions in each phase of the network as the final loss function:

\[
L_{all} = Loss_1 + Loss_2 + Loss_3 + Loss_4 + Loss_{GP} + Loss_{MS}
\]  

(4)

Different loss functions are used in different stages, among which, use the softmax loss with label smoothing regularization[15], and the rest use the batch hard triplet loss[16]. By calculating the weighted average and average distribution of the hard target in the dataset, the softmax loss with label smoothing regularization can effectively reduce overfitting on small sample data sets:

\[
L_{soft-LS} = -\frac{1}{N} \sum_{i=1}^{N} g_i \log((1-\varepsilon)p_i + \frac{\varepsilon}{S})
\]  

(5)

The traditional triples loss[17] randomly sample three pictures from the training data. For mining hard samples pairs, the batch hard triplet loss is proposed. And it enhances the compactness of intra-class and the separability of inter-class, which is defined as:

\[
L_{BT} = \sum_{i=0}^{p} \sum_{a=1}^{K} [m + \max_{j=1...p} D(f(I_i^a), f(I_j^a)) - \min_{n=1...K} D(f(I_i^a), f(I_n^a))]_+
\]  

(6)

### 4. Experiment and results

**4.1. Result**

In order to prove the superior performance of our method, we compare it with the best results at present. The specific results are as follows:

**Table 1.** Comparison of WRCAnet and other state-of-the-art methods on the Market-1501, DukeMTMC-ReID and CUHK03(Labelled and Detected) datasets. The bold are the best result.

| Method          | Market-1501 Rank-1 mAP | DukeMTMC-ReID Rank-1 mAP | CUHK03(L) Rank-1 mAP | CUHK03(D) Rank-1 mAP |
|-----------------|------------------------|--------------------------|----------------------|----------------------|
|                 |                        |                          |                      |                      |
### Market-1500
From Table 1, our model achieves relatively advanced performance mAP/Rank-1 = 87.8%/96.1%. By applying re-ranking [22], we can further get the better result that mAP and rank-1 are improved by 1.3% and 4.4%.

### On DukeMTMC-reID
It can be seen that although our results are not the best, our model achieves mAP/Rank-1 = 79.6%/87.5%. By applying re-ranking, we can further get the better result that mAP and rank-1 are improved by 5.3% and 3.8%.

### On CHUK03
The result of our model is much higher than that of other models on labeled (map/rank-1 = 78.7%/81.6%); on the detected dataset, we also get the result of map/rank-1 = 78.9%/81.4%.

### 4.2. Ablation study
As mentioned above, our method mainly consists of three parts: a) weak reverse attention; b) Multi-granularity Feature fusion module; and c) Multi-scale Feature fusion module. To evaluate the impact of each part on the experiment, we also performed additional experiments. We conducted the ablation study of model components on Market-1501 dataset to analyze the influence of the above components on the model.

| Model              | mAP  | Rank-1 | Rank-5 | Rank-10 |
|--------------------|------|--------|--------|---------|
| ResNet-50          | 71.4%| 87.5%  | 94.9%  | 96.7%   |
| ResNet-50+ WRA     | 78.9%| 90.2%  | 95.9%  | 97.3%   |
| ResNet-50+ WRA+GP  | 83.3%| 92.8%  | 97.0%  | 98.2%   |
| ResNet-50+ WRA+MS  | 86.2%| 93.5%  | 97.7%  | 98.3%   |
| ResNet-50+ WRA+MS+GP | 87.8%| 96.1%  | 98.5%  | 99.1%   |

The impact of WRA. Apply weak reverse attention (WRA) to resnet-50 as our backbone network. Comparing with resnet-50, we can find that without introducing more parameters than resnet-50, the mAP and Rank-1 of the ResNet-50+ WRA in this paper improved by 7.5% and 2.7%, respectively.

The impact of Multi-granularity Feature fusion. In the experiment, we added multi-granularity fusion branch to the main network and removed multi-granularity branch from the whole network. From the results in Table 2, we found that the network could improve from mAP/Rank-1 = 78.9%/90.2% to mAP/Rank-1 = 83.3%/92.8% after adding multi-granularity branches. And mAP and Rank-1 declined by 1.6% and 1.8%, respectively, after removing the multi-grained branches.

The impact of Multi-scale Feature fusion. As shown in Table 2, "resnet-50 + WRA+MS" is 7.3% and 2.8% higher than "resnet-50 + WRA". Simultaneously, As shown in Table 2, "resnet-50 + WRA+MS" improved by 7.3% and 2.6% compared with "resnet-50 + WRA", which decreased much more than the multi-granularity fusion module. It also shows to a certain extent that multi-scale fusion in this paper contributes more to the model than multi-granularity fusion.

### 5. Conclusion
For this paper, our aim is to introduce a new deep learning approach for person re-ID. We apply weak reverse attention mechanism, combined with content aware module which is composed of multi-
granularity and multi-scale to learn the global and local features of the picture without introducing image segmentation, attribute recognition and pose estimation, to achieve an end-to-end person re-recognition model. We conducted part estimation experiments on the market dataset, and conducted a large number of experiments on three mainstream public datasets, and the results proved that our method have achieved state-of-the-art results.

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