Multiscale Reference-Aided Attentive Feature Aggregation for Person Re-identification

LI XU\textsuperscript{1,2}, XIANG FU\textsuperscript{1,2}

\textsuperscript{1}Key Laboratory of Jiangxi Province for Image Processing and Pattern Recognition, Nanchang Hangkong University, Nanchang 330063, China
\textsuperscript{2}School of Software, Nanchang Hangkong University, Nanchang 330063, China

Corresponding author: Xiang Fu (fxb163@163.com)

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ABSTRACT In person re-identification (Re-ID), increasing the diversity of pedestrian features can improve recognition accuracy. In standard convolutional neural networks (CNNs), the receptive fields of neurons in each layer are designed to have the same size. Therefore, in complex pedestrian re-identification tasks, the standard CNNs extract local features but are unable to obtain satisfactory results for global features extracted from the images. Local feature learning methods are helpful for obtaining more abundant features, which focus on the most significant local features and ignore the correlations between features of various parts of the human body. To solve the above problems, a new multiscale reference-aided attentive feature aggregation (MS-RAFA) mechanism is proposed, consisting of three main modules. First, to extract the most significant local features and strengthen the correlations between the features of various parts of the human body, an autoselect module (ASM) is designed, an attentional mechanism that can stack the structural information and spatial relations to form new features. Then, to realize multiscale feature fusion of the multiple output branches of the backbone network and increase feature diversity, we propose a multilayer feature fusion module (MFFM), which enables the model to mine the features hidden by salient features and to learn features better. Finally, to supervise the MFFM and make the network obtain better recognition features, we propose a multiple supervision mechanism. Finally, experimental results demonstrate that our proposed method outperforms the state-of-the-art methods on three large-scale datasets.

INDEX TERMS Feature correlation; multiscale reference-aided; multilayer feature fusion; person re-identification

I. INTRODUCTION

Person re-identification (Re-ID), which forms the core of video surveillance technology, implements image processing, computer vision, pattern recognition, machine learning and other related technologies to solve cross-camera and cross-scene pedestrian retrieval problems. Re-ID utilizes the spatiotemporal continuity of images to continuously track pedestrians across cameras. Visual feature-based recognition methods are more reliable than those based on biological information, such as carrying items or clothing, and can be used more reliably in Re-ID [1,2,3,4]. With the popularity of video capture systems, video-based Re-ID also achieves more robust performance. Many scholars have developed improved pedestrian re-identification methods and achieved very good results. However, in cases involving different visual points, low image resolution, illumination changes, unconstrained attitude change and occlusion, the recognition effect is not ideal [5,6,7,8,9].

In recent years, deep learning, represented by convolutional neural networks (CNNs), has been successfully applied to the field of pedestrian re-recognition. CNNs are constructed by researchers with certain prior knowledge, and a large number of stacked convolutional cores are used to extract regional features. At present, there are many efficient feature extraction CNNs, such as GoogLeNet [10,11,12,13], ResNet [14], and VGGNet [15]. Feature extraction methods that implement feature learning algorithms can obtain better pedestrian representations. In the field of Re-ID, most algorithms use the feature of the last layer of the network to realize pedestrian recognition, which achieves good results but also has some defects [28]. Each CNN layer focuses on a different piece of information, low-level features such as...
Multiple monitoring mechanisms are used to supervise and model the object from a global scope. Additionally, features, which solves the problem of feature redundancy, are detection networks that need extra training, and when there is considerable background noise in the location, the ability of the model is poor, and the redundancy between features obtained from different regions is relatively high. (3) Methods based on automatic positioning attempt to locate body parts by learning a grid [20,21,22]. The above methods are detection networks that need extra training, and when there is considerable background noise in the location, the complexity of the whole model is increased.

To address the above deficiencies, in this paper we present a new multiscale reference-aided attentive feature aggregation (MS-RAFA) mechanism that enables the network to adaptively extract all potential salient pedestrian features. More specifically, we propose an autoselect module (ASM) to mine local and global information in different stages of the backbone network, which solves the problem of insufficient salient feature extraction. Then, we present a multilayer feature fusion module (MFFM), which is used to better aggregate the low- and high-level features of the backbone. The MFFM uses an adaptive selection mechanism to select effective features in different stages from multiscale features, which solves the problem of feature redundancy, and models the object from a global scope. Additionally, multiple monitoring mechanisms are used to supervise and teach the MFFM so that the network can obtain better identifying features. It is worth noting that the end-to-end training method is used, and no additional training network is required, reducing the complexity of the model. The specific content will be introduced in Section 3.

To summarize, our proposed work makes the following contributions:

- We introduce a novel multiscale reference-aided attentive feature aggregation mechanism (MS-RAFA) that can mine all potential salient features stage-by-stage and integrate these discriminative salience features with the global feature, forming the final diverse pedestrian feature representation.
- We devise an autoselect module (ASM), an attention mechanism placed on a backbone network that can optimize the backbone network features. This module extracts global and local appearance information compactly, stacks structural information and spatial relationships to form new features, and uses that information as input to the next stage.
- We incorporate a multilayer feature fusion module (MFFM) to extract and fuse low- and high-level features. The MFFM is a nonlinear dynamic selection mechanism that allows each neuron to adjust the size of its receptive field adaptively according to multiple input information scales.
- We propose a multiple supervision mechanism to verify the necessity of joining the MFFM and the final effect value of the network.
- Extensive experiments on CUHK03 [53], Market1501 [54] and DukeMTMC-ReID [55] demonstrate that our method significantly outperforms existing state-of-the-art methods.

II. RELATED WORK

Pedestrian re-recognition technology can be divided into five steps [27]: data collection, bounding box generation, training...
data annotation, model training and pedestrian retrieval. Due to the continuing improvements in computing power, many deep learning-based methods have been developed in recent years to solve pedestrian re-recognition tasks. This section will introduce the most representative works related to ours.

A. LOCAL FEATURE LEARNING

Varior R et al. [29] used a twin network to divide a pair of input images horizontally into several blocks. Then, several segmented image blocks were sent to a long short-term memory (LSTM) network in sequence [30], and the local features of all image blocks were fused to obtain the final feature representation. An image structure analysis method [31,32] was adopted to obtain the corresponding parts of features, such as head, chest, legs and shoes, and the color features of each part were extracted for matching. Zhang X et al. [33] designed a dynamic alignment network to automatically align image blocks from top to bottom. In terms of the spatial alignment of the human body, Zheng Z et al. [34] used spatial transformer networks (STNs) [35] to directly segment and align the original image. The STN was then also used to transform the shallow features extracted by CNNs to spatially align human body features. Reference [36] proposed a method of horizontal pyramid matching (HPM), which divides a pedestrian picture into 1, 2, 4 and 8 subparts horizontally. Reference [84] proposed a Multi-Granularity Network based on Local Context aware Correlation Feature (MGN_CACF) based on the ResNet50-IBN-a backbone, which is split into four branches.

Because local feature learning is only used to obtain and combine information of different parts of the human body, the trained network has insufficient generalizability. However, the information of each part of the human body has strong semantic correlations, which are helpful for teaching the network to learn better representation. If only part of the feature graph is learned, the correlation information between each part of the feature will be lost.

B. FINE-GRAINED INFORMATION LEARNING

One challenge in pedestrian recognition is distinguishing those with similar appearances. Reference [37] proposed a densely semantically aligned (DSA) model to map human body features to three-dimensional space. However, this method often requires both front and back pictures of the same person, which limits its applicability. Lin et al. [41] proposed a bilinear CNN model using two networks, VGG-D and VGG-M, as the joint benchmark network and achieved a good effect without using bounding box marking information. Reference [38] proposed an activation mapping method that judged the activation area by the loss function of the overlapping activation penalty to continuously expand the spatial perception range of the CNN. Reference [39] proposed an interaction-and-aggregation block (IA-Block), which can not only obtain pixel-level fine-grained information but also introduce channel information to obtain a more comprehensive feature representation. Reference [40] integrated attributes into features and proposed an attribute-driven feature separation and time-aggregated pedestrian re-recognition method. Reference [85] proposed leveraging the stability of person attributes to guide the learning of discriminative domain-invariant features (DIFs) and align attributes with corresponding local visual features.

Because the classification networks of these methods have strong feature representation ability, they can achieve better results in conventional image classification. However, in the study of Re-ID, the difference in some pedestrians' appearances is actually very subtle, so the effect is not ideal. The common solution is to use the network weights pretrained on ImageNet as the initial weights and then fine-tune them on a fine-grained classification dataset to obtain the final classification network.

C. ATTENTION MECHANISM LEARNING

The essence of the attention mechanism [42] is to imitate the human visual signal processing mechanism to selectively observe part of the area while ignoring other visible information. Li et al. [43] proposed a spatiotemporal attention model that uses multiple spatial attention models to ensure that each learns different parts of the body. Reference [44] used an attention diagram to determine whether an unnoticed area contains features that could provide a judgment basis to obtain complete human body features. Reference [45] proposed a pose-guided feature alignment (PGFA) method to obtain the features of the area where the body parts are connected. However, this method only focuses on unshaded parts and fails to identify shaded parts adequately. Reference [46] proposed a spatiotemporal completion network (STCNet) to solve the problem of pedestrian lower body occlusion. The spatial generator generates the frames that need to be completed, and then the temporal attention generator finds the adjacent key frames for completion. Reference [86] proposed a weighted aggregation strategy to impart a strong multiview reason ability to the imaginative reasoning module (IRM) and to classify and aggregate the single-view features of the same pedestrian.

Although the abovementioned attention mechanisms have achieved certain effects in pedestrian re-recognition, their main purpose is to extract the most significant features and suppress less obvious features. In this way, feature diversity is reduced, so the extracted features may be insufficient.

III. PROPOSED METHOD

We propose a new multiscale reference-aided attentive feature aggregation mechanism (MS-RAFA), which includes three main modules: the autosellect module (ASM), multilayer feature fusion module (MFFM) and the multiple supervision module. The framework is shown in Figure 2. ASM is an attentional mechanism and sits on a backbone network, which is used to solve the problem of insufficient feature extraction of the backbone network. MFFM operates...
the output features of each layer of the backbone network and selects useful information for fusion to obtain more features. The multiple supervision module supervises the optimization direction of the MFFM module and guides the MFFM to select effective pedestrian features for fusion.

A. AUTOSELECT MODULE

The goal of Re-ID is to recognize the same pedestrians from multiple cameras, but often the differences among these people are not sufficiently large. Most pedestrians are distinguished by clothing color, height, belongings and other information. The convolutional unit in a CNNs only focuses on the region of the convolutional kernel in the neighborhood each time. Although the receptive field becomes increasingly larger in later periods, it still learns from information in the local region, thus neglecting the contribution of other global regions to the current region. If the use of only local information cannot obtain the differences between objects well, the correlation between the features of various parts of the human body will be ignored, limiting the ability to improve the performance of the model. However, global learning extracts features from the global information of each pedestrian picture. These features have no spatial information and can easily lose details, which is not conducive to pedestrian recognition.

Considering the above, this paper proposes an ASM that uses the channel attention mechanism to obtain local information. Then, global average pooling is used to obtain global information. The local and global information are superimposed to obtain more accurate pedestrian information. Through these operations, effective object features can be better selected. The specific ASM structure is shown in the red dotted box in Figure 2. The ASM is placed into the backbone branch to compensate for its insufficient feature extraction ability.

Given an intermediate feature tensor of width W, height H, and channel number C in CNN layer \( X \in \mathbb{R}^{C \times H \times W} \), after the ASM has conducted a series of operations, a new feature graph \( F \) of size \( C \times H \times W \) is obtained. \( y_{\alpha}, y_{\beta}, y_{\gamma}, \text{and} \ y_{\delta} \) are all theoretically \( 1 \times 1 \) convolutions that can flexibly change the dimensions of the data. After the size of \( y_{\alpha} \) is changed to \( C \times W \times H \), the size of \( y_{\beta} \) and \( y_{\gamma} \) are changed to \( C \times H \times W \), \( y_{\delta} \) changes size to \( 1 \times C \times 1 \), and \( y_{\epsilon} \) changes size to \( 3 \times C \times 1 \). The \( 1 \times 1 \) convolution has different effects in different locations. Its main purpose is to multiply or add the features of the same input, increase the similarity and extract features. At the end of the module output, the sigmoid activation function is added to increase the nonlinear expression ability of the module and make the model more consistent with the data.

In Re-ID, it is possible to compute the global attention by using local convolutional operations. The main operation of the ASM is to take the C-dimensional eigenvector of each spatial position as a feature node, each of which uses the similarity relation function \( f = R(x, y) \) to obtain the similarity between features of other location nodes and form raster data.

Through raster scanning of spatial positions, \( N \) feature nodes are expressed as feature set \( V = \{ X_i \in \mathbb{R}^{C}, i = 1, \ldots, N \} \). The similarity relation \( R_{i,j} \) between any two nodes \( i \) and \( j \) in set \( V \) can be defined as the dot product similarity between the nodes:

\[
R_{i,j} = f(x_i, x_j) = \alpha(x_i) \cdot \omega \cdot \beta(x_j)
\]

(1)

where \( \alpha \) and \( \beta \) are two embedded functions shared between feature nodes, and \( \omega \) is an operation function for changing the size of the image. We first transform the input tensor \( X^{C \times H \times W} \) into \( X_t \in \mathbb{R}^{C \times W \times H} \), then implement \( 1 \times 1 \) convolution and BN layer, and finally activate the ReLU function to transform \( X_t \). We obtain and use the affinity matrix \( R_{i,j} \in \mathbb{R}^{C \times C \times 1} \) to represent the pairable relations of all nodes and then transform these pairable relations to obtain the global features. The local information of the C-dimensional feature vector of each spatial position can be obtained by the ASM module:

\[
L_{0,i} = \alpha \cdot x_i \cdot \psi_i
\]

(2)

where \( \alpha \) is the \( 1 \times 1 \) convolution function and \( \psi_i \) is an adaptive average pooling function. After the operation, the input tensor \( X^{C \times H \times W} \) is changed to \( X_t^{C \times 1 \times 1} \).

Global scopes contain rich structural and semantic information, while local features contain the most significant information. Using the ASM, they can be stacked, and valuable knowledge can be mined to infer spatial attention. Then, the spatial concern value of the \( i \)-th feature node \( G_i \) obtained through the modeling function, is defined as:

\[
G_i = \text{Sigmoid}(\alpha \cdot B \cdot R)
\]

(3)

where \( B \) is the BN function and \( R \) represents the ReLU operation. The sigmoid function causes the output to take on a value between 0 and 1. As a result, the weight of each feature in the spatial structure is different, and the probability of the feature that needs to be given more attention is larger, which is conducive to feature extraction and model learning.

To learn the attention of the \( i \)-th and \( j \)-th feature nodes, in addition to the pair relation term \( R_{i,j} \), the feature \( X_t \) is added. Using the global scope structure information and local original information related to this feature, the final output \( \tilde{F} \) can be expressed as:

\[
\tilde{F}_{i,j} = [G_i, X_t]
\]

(4)

Experimental results show that the ASM proposed in this paper can effectively extract the global and local hidden features. Moreover, it can be used in different neural network frameworks. Most importantly, it can improve Re-ID accuracy.

B. MULTILAYER FEATURE FUSION MODULE

Fusion and analysis of features at different levels [47] can help in semantic segmentation, classification and detection. Common fusion operations are performed at the pixel level, such as addition or concatenation, but the performance gains are limited and lack semantic information. To aggregate features at different scales from different branches and retain
Figure 2. Multiscale reference-aided attentive feature aggregation mechanism. After modifying the ResNet50 backbone, we adopt several separate feature autoselection phases. In the training process, ID loss and triplet loss are used to supervise the learning in the two stages, and the final loss is the sum of the two supervision losses. In the test, the features of all the different stages are linked together as the final pedestrian descriptor image.

The input of the MFFM is the output feature of the ASM in each stage of the backbone network. In a CNNs, the bottom layer contains shallow information such as position and shape information, while the top layer contains deep semantic information. To obtain effective pedestrian information at different stages, we proposed the MFFM method to fuse these different depths of information. The MFFM is a nonlinear module that can dynamically select features. It allows the input of multiple neurons of different sizes, each of which adjusts the size of its acceptance domain according to the information scale, and then outputs features of uniform size.

As shown in Figure 2, the backbone network is divided into five layers, each with different sizes and information. Except for the first layer, the other four layers are followed by an ASM. Features that pass through the ASM are the source of the multilayer features that will enter the MFFM. In Figure 3, $P_2$-$P_5$ represents the multilayer feature input, in which the lower-level feature map is larger and contains more feature information, while the higher-level feature map is smaller in size but with a larger object. The study found that as the object grows larger, most neurons gather more information from the larger kernel pathway. This suggests that the nonlinear dynamic selection mechanism in the MFFM has superior performance in object recognition, which enables neurons to adaptively adjust their receptive field size. $P_2$-$P_5$ are convolved to change the number of channels and the size of the feature map so that the output feature, denoted as $C_i$ ($i=3,4,5$), is uniform in size. For the input, a given intermediate feature tensor $P_2 \in \mathbb{R}^{C_2 \times H \times W}$ with width $W$, height $H$, and number of channels $C$ is:

$$
C_2 = \text{Relu}\left( W_1 \cdot \text{Maxpool}_{2d} \cdot W_2 \cdot P_2 \right),
$$

$$
C_3 = \text{Relu}\left( W_1 \cdot W_2 \cdot P_3 \right),
$$

$$
C_4 = \text{Relu}\left( W_2 \cdot P_4 \right),
$$

$$
C_5 = \text{Relu}\left( W_2 \cdot P_5 \right)
$$

where $W_1$ and $W_2$ are implemented by convolution followed by BN. The final size of $C_i$ is the same as that of $P_4$, therefore, the feature map tensor $C_i \in \mathbb{R}^{C_i \times H_i \times W_i}$ is obtained by taking the size of $P_4$ as the standard.

After unifying transformation to obtain the same size, to highlight the significant features, we add $C_i$ elementwise to form a new aggregation feature $L$, which combines low- and high-level features. Then, $FC1$ uses global average pooling to operate on $L$, and the generated channel statistics are embedded in the global information. Here the input $L \in \mathbb{R}^{C \times H \times W}$, and the output $FC1 \in \mathbb{R}^{C \times 1 \times 1}$. Specifically, the elements in $FC1$ are calculated by spatial dimension contraction of $L$:

$$
FC1 = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} L(i, j)
$$

Furthermore, a compact feature $FC2 \in \mathbb{R}^{d \times c}$ is created, which is attenuated by $FC1$ to achieve precise and adaptive selection guidance. This is achieved through a simple convolutional layer, which improves efficiency by reducing dimensions:

$$
FC2 = \alpha \cdot B \left( R \cdot FC1^{d \times c} \right)
$$
where $a$ denotes $1 \times 1$ convolution, $B$ denotes BN, and $R$ is the ReLU operation. To study the effect of dimension $d$ on model efficiency, we use a reduction ratio $r$ to control its value:

$$d = \max(C / r, m)$$  \hspace{1cm} (8)

where $m$ represents the minimum value of $d$ ($m=256$ is fixed in our experiment), $r$ is set to 4, and then the feature vector is expanded to the size of the feature before attenuation.

The FC1 and FC2 operators combine and aggregate the information from multiple paths to obtain a global and comprehensive representation for the selection weights. Next, the weight $FC_i$ of each channel is obtained through a softmax operation (in which the importance is expressed by the probability of each channel). Then, $FC_i$ is multiplied with the original feature $Ci$ to obtain the feature weight of each channel. This is the equivalent of a select operation, it aggregates the feature maps of differently sized kernels according to the selection weights. Finally, the weight feature map obtained is added element by element, and the final weight feature $V$ is obtained through the multilayer feature fusion module as:

$$V = Cat(Ci \ast fc_i), \hspace{0.5cm} i = 2,3,4,5$$  \hspace{1cm} (9)

The size of the feature map of $V$ is the same as that of the output feature graph of the last layer of the backbone network. Through this soft attention method, adaptive kernel selection is performed to obtain the potentially significant features among the global features, increasing feature diversity and improve object recognition efficiency and effectiveness.

C. MULTIPLE SUPERVISION MECHANISM

As shown in Figure 2, to increase the information diversity and improve information interactivity, the features output from the MFFM and the last ASM are added elementwise to form a new feature, $X_{ap} \in R^{C \times H \times W}$, with twice the number of channels. Then, the feature map tensor $V \in R^{C \times H \times W}$ output from the MFFM module and the feature tensor $x \in R^{C \times H \times W}$ output from the backbone network are combined by the add operation. The subsequent $1 \times 1$ convolution changes the number of channels from $2C$ to $C$ to reduce the number of channels in the feature map. Previously, the fully connected layer FC had been used for information classification, but its computational complexity is high. Therefore, we replace it with global average pooling, which calculates a weighted sum of the front layer features, takes the internal average of each feature map, and turns each feature map into a value.

The MFFM aggregates multiscale pedestrian features to obtain more robust information. The feature information involved in this module is quite different, aggregating these features will not achieve good recognition performance. Therefore, a multiple monitoring mechanism that uses real pedestrian information to monitor the MFFM and adaptively select effective information is designed. As shown in Table 8, an ablation experiment demonstrates that supervision is necessary. After obtaining the features supervised by the MFFM, the multiple supervision mechanism is merged with the features of the backbone network for the last layer, and then another supervision is implemented.

We add two loss functions to the final effect value of the monitoring network. The identification loss function obtains the predicted logit value of the image, similar to the classification loss, and is defined as:

$$L_{id} = \sum_{i=1}^{N} - q_i \log(p_i)$$  \hspace{1cm} (10)

where $y$ and $p_i$ represent the real ID tag and predicted logit value of the classification, respectively. $N$ represents the number of classes, $q_i$ is the proposed smoothing label and $\varepsilon=0.1$ [83]. Considering the goal of Re-ID, which is to find the most similar sequences of people from a gallery of images, the idea of metric learning is introduced to enable networks to find useful features for similarity measurement. Therefore, triplet loss is adopted to improve the final ranking performance, which is defined as:

$$L_{ap} = \sum_{N} \left[d_{pos} - d_{neg}\right]_+$$  \hspace{1cm} (11)

where $d_{pos}$ is the feature distance of the same identity and $d_{neg}$ is the distance of different identities. $N$ is the batch size of the triplet samples, and $[\cdot]_+$ represents $\max(\cdot, 0)$. The purpose of triplet loss is to ensure that the distance between the positive sample pairs is less than the distance between the negative sample pairs. Here, it ensures that the distance between similar features and the positive sample is close. Note that

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**FIGURE 3. Multilayer Feature Fusion Module**

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the distance is measured by the Euclidean distance in the
design of this paper.

In this paper, the model undergoes supervised learning

twice, first for the features obtained by the MFFM and
second for the fusion features of the last layer of the
backbone network. The final total loss of the model is the
sum of the two losses and can be written as:

\[
Loss = L_{id} + L_{tpi} \quad (i = 1, 2)
\]  

(12)

where \(i\) indicates the \(i\)-th supervised learning. Finally, the
monitoring mechanism is used to supervise the results and
verify the effectiveness of the proposed method.

IV. EXPERIMENTS

A. EXPERIMENTAL DETAILS

We use ResNet50 as our backbone network. The total batch
size is set to 64, and two GPU graphics cards are shared. The
batch size on each graphics card is set to the value that
automatically divides the total batch size.

We use common data augmentation strategies: random
clipping [50], horizontal flipping and random erasure [51].
The input of all datasets is changed to images with a uniform
size of 256×128, and the backbone network is pretrained on
ImageNet [52]. Using the Adam optimizer, all models are
trained with a total of 600 epochs, the recording of
parameters starts from epoch=320, and a new file is recorded
every 40 epochs. The learning rate is 8×10^{-4}, and the weight
decay is 5×10^{-4}.

The experiment is performed on three public re-
identification datasets: CUHK03 [53], Market1501 [54] and
DukeMTMC-ReID (a subset of the DukeMTMC [55]
dataset). The details of the datasets are shown in Table 1. To
compare the performance of this method with that of existing
Re-ID methods, we use the rank index in cumulative
matching characteristics (CMC) and mean average precision
(mAP) as the evaluation index of each queried image.

B. EXPERIMENTAL RESULTS

In this section, the final experimental results for the proposed
method on different datasets are highlighted and compared
with the results for other methods.

Table 2 shows the results of different methods on the
Market1501 dataset. Note that all methods listed in the table
are based on the ResNet50 backbone network. i) The
methods are from different journals and published in
different years. The oldest papers were published in 2018,
and the latest were published in 2021. ii) Our experimental
results are superior to those of other methods, in terms of
both mAP and Rank-1 accuracy. Our mAP value is 89.1%,
and the Rank-1 accuracy is 95.8%. The mAP value was 5.4% higher than the baseline, while the Rank-1 value was 1.6% higher.

CUHK03 is a more challenging dataset than Market1501 and
DukeMTMC-ReID. This is because i) CUHK03 has
fewer samples and contains serious viewpoint variations and
occlusion problems; and ii) the annotation of bounding boxes
marked by the object detection algorithm has location offsets.
All methods listed in Table 3 are also based on the ResNet50
backbone network. The experimental results of our method,
both mAP and Rank-1, are significantly better than those of
the other methods. The mAP and Rank-1 values for the
labelled category are 79.6% and 83.9%, which are 10.6% and
10.1% higher than the baseline, respectively. The mAP and
Rank-1 values of the detected category are 77.2% and 82.2%,
respectively, which are 11.7% higher than both the mAP and
Rank-1 of the baseline.
Table 4 shows the results of the different methods on the DukeMTMC-ReID dataset. To further verify the effectiveness of our method, we select methods with different backbone networks, for example, ResNet101, DenseNet121 and SEResNet101. Similar to the other two datasets, the proposed MS-RAFA also achieves the best results in terms of Rank-1 accuracy and mAP. Our results exceed those of MGN_CACF[86](21) by 0.4%.

Through these comparisons, it can be seen that the method proposed in this paper is the most effective. The experimental results clearly demonstrate that mining potential features and integrating these complementary features leads to great performance advantages.

C. ABLATION EXPERIMENT

To demonstrate the experimental results of our MS-RAFA, we conduct an incremental evaluation of its modules on the Market1501 dataset. The dataset consists of complex scenes and contains much information, so the experimental results when testing our model are more convincing. We again use ResNet50 as the backbone network. In Figure 2, the MFFM module fuses the output of the four layers after the output of that contain the ASM module. After that, the feature V outputted from the MFFM module is fused with the feature outputted through the backbone network (which we simply denote as x). Finally, it is supervised by ID and triplet loss twice. It is worth noting that the final total loss is the sum of the two supervised losses.

To better verify the experimental effect of each module on the overall network, we conduct experiments on each module, and the results are shown in Table 5. For the three modules, the result of removing any one module is lower than the result of combining them all together, which shows that the three modules are complementary. After implementing the ASM, the mAP value improved by 1.4%, which shows that the module leads to the extraction of more effective target features through the identification of local and global features. After implementing the MFFM, the mAP value improved by 0.9%. This is because the MFFM can make reasonable use of both high- and low-level features. The two proposed modules complement each other and extract more hidden features. After using the multiple supervision module, the mAP value improved by 0.3%. This indicates that multiple supervision helps detect and teach the MFFM to obtain better recognition features. Therefore, this reasonably demonstrated the validity of our three proposed modules.

The feature map outputted by the first layer of the ResNet50 network model is very large (7x7 convolution), contains very complex information, and has a large number of parameters and a large number of computations. Therefore, we do not add the ASM after the first layer, as shown in the red dotted box in Figure 2. Instead, ASM modules are added after the last four layers (i.e., layer2, layer3, layer4 and layer5).
The Grad-CAM masks of our proposed model cover the human area better than the baseline model, allowing the network to focus on larger regions of different parts of the body. Compared with RGA [56], which uses spatial and channel attention mechanisms, our method more clearly reflects the extraction of more salient and implicit features. This is the result of the aggregation and mining of multiscale attention features from global-scale structural information.

### V. CONCLUSIONS

For the re-identification of pedestrians, a new multiscale reference-aided attentive feature aggregation (MS-RAFA) mechanism was proposed to learn more distinct features. First, to extract the most significant local and global features and strengthen the correlation between the features of various parts of the human body, an attention mechanism called the autoselection module (ASM) was designed. Then, to extract and fuse low- and high-level features, an multilayer feature fusion module (MFFM) was proposed. The MFFM is an complementary. Specifically, the MFFM module acquires features of different levels and integrates them into a new feature. It is effective because the formation of new features has a certain positive effect on the extraction of global features. It also forms information complementarity between different layers to obtain more implicit features.

To verify the fusion of the $V$ and $x$ features, as well as the effectiveness of the supervision of ID and triplet loss twice, we set up a comparison experiment, as shown in Table 8, where w/o VLoss and w/o xloss represent removal of the corresponding loss, xvCat represents the fusion operation on the output features of the MFFM and the features of the last layer of the backbone network, and both refers to the complete multiple supervision mechanism. After using VLoss, the mAP value improves by 1.8%, and after using xLoss, the mAP value improves by 1.4%. Therefore, adoption of both branches is most effective for loss supervision and information fusion. The mAP and Rank-1 values for this condition are the best in the comparative experiment.

### D. VISUALIZATION OF ATTENTION

Similar to RGA[56], we apply the Grad-CAM (gradient-weighted class activation mapping) [82] tool to the baseline model and to our model for qualitative analysis. The Grad-CAM tool identifies areas that the network deems important, as shown in a comparison between the models in Figure 4. The Grad-CAM masks of our proposed model cover the human area better than the baseline model, allowing the network to focus on larger regions of different parts of the body. Compared with RGA [56], which uses spatial and channel attention mechanisms, our method more clearly reflects the extraction of more salient and implicit features. This is the result of the aggregation and mining of multiscale attention features from global-scale structural information.

### TABLE 5. Impact of each module on network performance (%) and MS: multiple supervision module

| Method | mAP | Rank-1 | Rank-5 | Rank-10 |
|--------|-----|--------|--------|---------|
| ASM    | -   | -      | -      | -       |
| MFFM   | -   | -      | -      | -       |
| MS     | 83.7| 94.2   | 98.6   | 99.1    |
| w/o layer5 | 88.5| 95.5   | 98.6   | 99.1    |
| w/o layer54 | 87.2| 95.2   | 98.6   | 99.1    |
| w/o layer543 | 87.0| 95.3   | 98.6   | 99.1    |
| w/o layer5432 | 88.2| 95.5   | 98.6   | 99.1    |
| All    | 89.1| 95.8   | 98.7   | 99.1    |

### TABLE 6. Experimental results from imposing internal changes to the ASM (%) and the effectiveness of the global relation representation (Rel.) and the feature itself (Ori.). w/o: without.

| Method | mAP | Rank-1 | Rank-5 | Rank-10 |
|--------|-----|--------|--------|---------|
| w/o Rel. | 87.5| 95.5   | 98.6   | 99.1    |
| w/o Ori. | 88.1| 95.4   | 98.6   | 99.2    |
| Both   | 89.1| 95.8   | 98.7   | 99.1    |

### TABLE 7. Internal ablation experiment on the MFFM module(%) and w/o: without.

| Method | mAP | Rank-1 | Rank-5 | Rank-10 |
|--------|-----|--------|--------|---------|
| w/o layer5 | 87.5| 95.5   | 98.2   | 98.9    |
| w/o layer54 | 87.2| 95.2   | 98.6   | 99.1    |
| w/o layer543 | 87.0| 95.3   | 98.6   | 99.1    |
| w/o layer5432 | 88.2| 95.5   | 98.6   | 99.1    |
| All    | 89.1| 95.8   | 98.7   | 99.1    |

Table 6 shows the results on ablation experiments on the ASM structure to verify its effect on model performance. For learning attention, without taking the proposed global relation (Rel.) as part of the input, the scheme is inferior to our scheme that includes the ASM by 1.6% in mAP. In addition, without taking the feature itself (Ori.) as part of the input, the scheme is inferior to our ASM scheme by 1.0% in mAP. The combination of the two structures achieves better performance. This suggests that the main improvement in the experimental results comes from the new design for learning attentional relations, in which modeling of global relations provides better performance.

To further verify the fusion effectiveness of the MFFM module, we implement the following experiments with internal detail changes, and its results are shown in Table 7. The MFFM module fuses the output of the four layers that contain the ASM module. Here, we remove some of the fusion branches to verify the fusion effectiveness of the MFFM on the low- and high-level features. The terms w/o layer5, w/o layer54, w/o layer543, and w/o layer5432 indicate removal of the corresponding fused layers in turn. For example, w/o layer54 indicates that the output of the branches of the fifth and fourth layers do not enter the MFFM module for fusion. w/o layer543 is equivalent to using only the ASM in the model.

In Table 7, as the number of fusion layers decreases, the performance of the model gradually decreases. The decreases by 2.1%, and the Rank-1 value decreases by 0.6%, which indicates that the information inside the MFFM module is...
independent branch that fuses each layer of output from the combination of backbone networks, which enables the model to extract hidden features concealed by salient features and to learn them better. Finally, the effectiveness of the model was verified by multiple supervision mechanisms to obtain better model performance. Extensive ablation studies demonstrated the high efficiency and state-of-the-art performance of our design.

REFERENCES

[1] Y. Liu, Z. Yuan, W. Zhou, and H. Li, “Spatial and temporal mutual promotion for video-based person re-identification,” in Proceedings of the AAAI Conference on Artificial Intelligence, 2019, vol. 33, no. 01, pp. 8786-8793.

[2] W. Li, X. Zhu, and S. Gong, “Harmonious attention network for person re-identification,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 2285-2294.

[3] C. Wang, Q. Zhang, C. Huang, W. Liu, and X. Wang, “Mancs: A multi-task attentional network with curriculum sampling for person re-identification,” in Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 365-381.

[4] L. Zhao, X. Li, Y. Zhuang, and J. Wang, “Deeply-learned part-aligned representations for person re-identification,” in Proceedings of the IEEE international conference on computer vision, 2017, pp. 3219-3228.

[5] Y. Wang, L. Wang, Y. You, X. Zou, V. Chen, S. Li, G. Huang, B. Hariharan, and K. Q. Weinberger, “Resource aware person re-identification across multiple resolutions,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 8042-8051.

[6] Y. Huang, Z.-J. Zha, X. Fu, and W. Zhang, “Illumination-invariant person re-identification,” in Proceedings of the 27th ACM International Conference on Multimedia, 2019, pp. 365-373.

[7] M. S. Sarfraz, A. Schumann, A. Eberle, and R. Stiefelhagen, “A pose-sensitive embedding for person re-identification with expanded cross neighborhood re-ranking,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 420-429.

[8] H. Huang, D. Li, Z. Zhang, X. Chen, and K. Huang, “Adversarially occluded samples for person re-identification,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 5098-5107.

[9] R. Hou, B. Ma, H. Chang, X. Gu, S. Shan, and X. Chen, “Vrsc: Occlusion-free video person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 7183-7192.

[10] C. Szegedy et al., “Going deeper with convolutions,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 1-9.

[11] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, “Rethinking the inception architecture for computer vision,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 2818-2826.

[12] S. Ioffe, and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” in International Conference on Machine Learning, 2015, pp. 448-456.

[13] Szegedy C , Ioffe S , Vanhoucke V , et al. “Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning”, 2016.

[14] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 770-778.

[15] K. Simonyan, and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” 2014, arXiv:1409.1556. [Online]. Avilable: https://arxiv.org/abs/1409.1556.

[16] Y. Sun, L. Zheng, Y. Yang, Q. Tian, and S. Wang, “Beyond part models: Person retrieval with refined part pooling (and a strong convolutional baseline),” in Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 480-496.

[17] G. Wang, Y. Yuan, X. Chen, J. Li, and X. Zhou, “Learning discriminative features with multiple granularities for person re-identification,” in Proceedings of the 26th ACM International Conference on Multimedia, Oct. 2018, pp. 274-282.

[18] X. Zhang, H. Luo, X. Fan, W. Xiang, Y. Sun, Q. Xiao, W. Jiang, C. Zhang, and J. Sun, “Alignedreid: Surpassing human-level performance in person re-identification,” in Proceedings of the 26th ACM International Conference on Multimedia, Oct. 2018, pp. 274-282.

[19] X. Zhang, H. Luo, X. Fan, W. Xiang, Y. Sun, Q. Xiao, W. Jiang, C. Zhang, and J. Sun, “Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning”, 2016.

[20] X. Zhang, H. Luo, X. Fan, W. Xiang, Y. Sun, Q. Xiao, W. Jiang, C. Zhang, and J. Sun, “Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning”, 2016.

[21] X. Zhang, H. Luo, X. Fan, W. Xiang, Y. Sun, Q. Xiao, W. Jiang, C. Zhang, and J. Sun, “Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning”, 2016.
[24] W. Yang, H. Huang, Z. Zhang, X. Chen, K. Huang, and S. Zhang, “Towards rich feature discovery with class activation maps augmentation for person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 1389-1398.

[25] M. Zheng, S. Karanam, Z. Wu, and R. J. Radke, “Re-identification with consistent attentive siamese networks,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 5735-5744.

[26] W. Li, X. Zhu, and S. Gong, “Harmonious attention network for person re-identification,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 2285-2294.

[27] M. Ye, J. Shen, G. Lin, T. Xiang, L. Shao, and S. C. Hoi, “Deep learning for person re-identification: A survey and outlook,” IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021.

[28] F. Wang, C. Zhang, S. Chen, G. Ying, and J. Lv, “Engineering Hand-designed and Deeply-learned features for person Re-identification,” Pattern Recognition Letters, vol. 130, pp. 293-298, 2020.

[29] R. R. Varior, B. Shuai, J. Lu, D. Xu, and G. Wang, “A siamese long short-term memory architecture for human re-identification,” in European Conference on Computer Vision, Sep. 2016, pp. 135-153.

[30] S. Hochreiter, and J. Schmidhuber, “Long short-term memory,” Neural computation, vol. 9, no. 8, pp. 1735-1780, 1997.

[31] D. S. Cheng, and M. Cristani, “Person re-identification by articulated appearance matching,” in Person Re-Identification: Springer, 2014, pp. 139-160.

[32] D. S. Cheng, M. Cristani, M. Stoppa, L. Bazzani, and V. Murino, “Custom pictorial structures for re-identification,” in Bmvc, 2011, vol. 1, no. 2: Citeseer, p. 6.

[33] X Zhang, H Luo, and X Fan, “Alignedreid: Surpassing human-level performance in person re-identification,” 2017, arXiv:1711.08184, [Online]. Available: https://arxiv.org/abs/1711.08184.

[34] Z. Zheng, L. Zheng, and Y. Yang, “Pedestrian alignment network for large-scale person re-identification,” IEEE Transactions on Circuits and Systems for Video Technology, vol. 29, no. 10, pp. 3037-3045, 2018.

[35] M. Jaderberg, K. Simonyan, and A. Zisserman, “Spatial transformer networks,” advances in Neural Information Processing Systems, vol. 28, pp. 2017-2025, 2015.

[36] Y Fu, Y Wei, and Y Zhou, “Horizontal pyramid matching for person re-identification,” in Proceedings of the AAAI Conference on Artificial Intelligence, 2019, vol. 33, no. 01, pp. 8295-8302.

[37] Z. Zhang, C. Lan, W. Zeng, and Z. Chen, “Densely semantically aligned person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 667-676.

[38] W. Yang, H. Huang, Z. Zhang, X. Chen, K. Huang, and S. Zhang, “Towards rich feature discovery with class activation maps augmentation for person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 1389-1398.

[39] R. Hou, B. Ma, H. Chang, X. Gu, S. Shan, and X. Chen, “Interaction-and-aggregation network for person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 9317-9326.

[40] Y. Zhao, X. Shen, Z. Jin, H. Lu, and X.-s. Hua, “Attribute-driven feature disentangling and temporal aggregation for video person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 4913-4922.

[41] X. Zhang, F. Zhou, Y. Lin, and S. Zhang, “Embedding label structures for fine-grained feature representation,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 1114-1123.

[42] T. Xiao, Y. Xu, K. Yang, J. Zhang, Y. Peng, and Z. Zhang, “The application of two-level attention models in deep convolutional neural network for fine-grained image classification,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 842-850.

[43] S. Li, S. Bak, P. Carr, and X. Wang, “Diversity regularized spatiotemporal attention for video-based person re-identification,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 542-551.

[44] R. Hou, B. Ma, H. Chang, X. Gu, S. Shan, and X. Chen, “Vrstc: Occlusion-free video person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 7183-7192.

[45] S. Lazebnik, C. Schmid, and J. Ponce, “Beyond bags of features: Spatial pyramid matching for recognizing natural scene categories,” in 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’06), 2006, vol. 2: IEEE, pp. 2169-2178.

[46] Z. Zhu, M. Xu, S. Bai, T. Huang, and X. Bai, “Asymmetric non-local neural networks for semantic segmentation,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 593-602.

[47] X. Li, W. Wang, X. Hu, and J. Yang, “Selective kernel networks,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 510-519.

[48] Yan Wang, Lequn Wang, Yusong You, Xu Zou, Vincent Chen, Serena Li, Gao Huang, Bharath Hariharan, and Kilian Q Weinberger, “Resource aware person re-identification across multiple resolutions,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 8042-8051.

[49] Z. Zhong, L. Zheng, G. Kang, S. Li, and Y. Yang, “Random erasing data augmentation,” in Proceedings of the AAAI Conference on Artificial Intelligence, 2020, vol. 34, no. 07, pp. 13001-13008.

[50] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, “Imagenet: A large-scale hierarchical image database,” in 2009 IEEE Conference on Computer Vision and Pattern Recognition, 2009, pp. 248-255.

[51] W. Li, R. Zhao, T. Xiao, and X. Wang, “Deep-reid: Deep filter pairing neural network for person re-identification,” in Proceedings of the
IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 152-159.

[54] L. Zheng, L. Shen, L. Tian, S. Wang, J. Wang, and Q. Tian, “Scalable person re-identification: A benchmark,” in Proceedings of the IEEE International Conference on Computer Vision, 2015, pp. 1116-1124.

[55] Z. Zheng, L. Zheng, and Y. Yang, “Unlabeled samples generated by gan improve the person re-identification baseline in vitro,” in Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 3754-3762.

[56] Z. Zhang, C. Lan, W. Zeng, X. Jin, and Z. Chen, “Relation-aware global attention for person re-identification,” in Proceedings of the ieee/cvf Conference on Computer Vision and Pattern Recognition, 2020, pp. 3186-3195.

[57] X Chen, C Fu, and Y Zhao, “Salience-guided cascaded suppression network for person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 3300-3310.

[58] X. Jin, C. Lan, W. Zeng, G. Wei, and Z. Chen, “Semantics-aligned representation learning for person re-identification,” in Proceedings of the AAAI Conference on Artificial Intelligence, 2020, vol. 34, no. 07, pp. 11173-11180.

[59] K. Zhu, H. Guo, Z. Liu, M. Tang, and J. Wang, “Identity-guided human semantic parsing for person re-identification,” in Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part III 16, Dec. 2020, pp. 346-363.

[60] Z. Cheng, Q. Dong, S. Gong, and X. Zhu, “Inter-task association critic for cross-resolution person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 2605-2615.

[61] J. Zhou, B. Su, and Y. Wu, “Online joint multi-metric adaptation from frequent sharing-subset mining for person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 2909-2918.

[62] X. Wang, R. Girshick, A. Gupta, and K. He, “Non-local neural networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 7794-7803.

[63] S. Woo, J. Park, J.-Y. Lee, and I. S. Kweon, “Cbam: Convolutional block attention module,” in Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 3-19.

[64] J. Hu, L. Shen, and G. Sun, “Squeeze-and-excitation networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 7132-7141.

[65] Y. Cao, J. Xu, S. Lin, F. Wei, and H. Hu, “Gcnet: Non-local networks meet squeeze-excitation networks and beyond,” in Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops, 2019, pp. 7132-7141.

[66] B. Chen, W. Deng, and J. Hu, “Mixed high-order attention network for person re-identification,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 371-381.

[67] P. Fang, J. Zhou, S. K. Roy, L. Petersson, and M. Harandi, “Bilinear attention networks for person retrieval,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 8030-8039.

[68] Z. Zheng, X. Yang, Z. Yu, L. Zheng, Y. Yang, and J. Kautz, “Joint discriminative and generative learning for person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 2138-2147.

[69] K. Zhou, Y. Yang, A. Cavallaro, and T. Xiang, “Omni-scale feature learning for person re-identification,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 3702-3712.

[70] Z. Dai, M. Chen, X. Gu, S. Zhu, and P. Tan, “Batch droblock network for person re-identification and beyond,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 3691-3701.

[71] G. A. Wang, S. Yang, and H. Liu, “High-order information matters: Learning relation and topology for occluded person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 6449-6458.

[72] B. Chen, W. Deng, and J. Hu, “Mixed high-order attention network for person re-identification,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 371-381.

[73] M. Zheng, S. Karanam, Z. Wu, and R. J. Radke, “Re-identification with consistent attentive siamese networks,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 5735-5744.

[74] L. T. Almeu, M. Pelillo, and M. Shah, “Deep constrained dominant sets for person re-identification,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 9855-9864.

[75] C.-P. Tay, S. Roy, and K.-H. Yap, “Aanet: Attribute attention network for person re-identifications,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 7134-7143.

[76] M. S. Sarfraz, A. Schumann, A. Eberle, and R. Stiefelhagen, “A pose-sensitive embedding for person re-identification with expanded cross neighborhood re-ranking,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 420-429.

[77] R. Hou, B. Ma, H. Chang, X. Gu, S. Shan, and X. Chen, “Interaction-and-aggregation network for person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 9317-9326.

[78] Y. Sun et al., “Perceive where to focus: Learning visibility-aware part-level features for partial person re-identification,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 393-402.

[79] M. M. Kalayeh, E. Basaran, M. Gökmen, M. E. Kamasak, and M. Shah, “Human semantic parsing for person re-identification,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 1062-1071.

[80] F. Hong, D. Huang, and G. Chen, “Interaction-aware factorization machines for recommender systems,” in Proceedings of the AAAI Conference on Artificial Intelligence, 2019, vol. 33, no. 01, pp. 3804-3811.

[81] H. Huang, D. Li, Z. Zhang, X. Chen, and K. Huang, “Adversarially occluded samples for person re-identification,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 5098-5107.

[82] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, “Grad-cam: Visual explanations from deep networks via gradient-based localization,” in Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 618-626.
[83] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna, “Rethinking the inception architecture for computer vision,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016.

[84] Y. Hou, C. Chen and Y. Li, “Efficient Multi-Granularity Network based on Local Context-aware Correlation Feature for Person Re-Identification,” 2021 6th International Conference on Intelligent Computing and Signal Processing (ICSP), 2021, pp. 553-556, doi: 10.1109/ICSP51882.2021.9408832.

[85] H. Li, Y. Chen, D. Tao, Z. Yu and G. Qi, “Attribute-Aligned Domain-Invariant Feature Learning for Unsupervised Domain Adaptation Person Re-Identification,” in IEEE Transactions on Information Forensics and Security, vol. 16, pp. 1480-1494, 2021, doi: 10.1109/TIFS.2020.3036800.

[86] H. Li, N. Dong, Z. Yu, D. Tao and G. Qi, “Triple Adversarial Learning and Multi-view Imaginative Reasoning for Unsupervised Domain Adaptation Person Re-identification,” in IEEE Transactions on Circuits and Systems for Video Technology, doi: 10.1109/TCSVT.2021.3099943.

[87] X. Wu, B. Xie, Y. Zhang, S. Zhao and S. Zhang, “Construction of Diverse DropBlock Branches for Person Re-Identification,” in IEEE Transactions on Cognitive and Developmental Systems, 2021, doi: 10.1109/TCDS.2021.3096546.

[88] X. Fan, J. Zhang and Y. Lin, “Person Re-IDentification based on mutual learning with embedded noise block,” in IEEE Access, 2021, doi: 10.1109/ACCESS.2021.3102450.

[89] M. Fu et al., “Improving Person Re-identification using A Self-focusing Network in Internet of Things,” in IEEE Internet of Things Journal, 2021, doi: 10.1109/JIOT.2021.3084978.

[90] K. Zhou, Y. Yang, A. Cavallaro and T. Xiang, “Learning Generalisable Omni-Scale Representations for Person Re-Identification,” in IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021, doi: 10.1109/TPAMI.2021.3069237.

LI XU is currently pursuing a master’s degree at Nanchang Hangkong University. His research interests include computer vision, image processing and person re-identification.

XUANG FU received his Ph.D. from Xidian University in 2008. He is now an associate professor at Nanchang Hangkong University. His research fields are computer vision, image processing and pattern recognition.