**SCAN: Self-and-Collaborative Attention Network for Video Person Re-identification**

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Abstract

Video person re-identification attracts much attention in recent years. It aims to match image sequences of pedestrians from different camera views. Previous approaches usually improve this task from three aspects, including a) selecting more discriminative frames, b) generating more informative temporal representations, and c) developing more effective distance metrics. To address the above issues, we present a novel and practical deep architecture for video person re-identification termed Self-and-Collaborative Attention Network (SCAN). It has several appealing properties. First, SCAN adopts non-parametric attention mechanism to refine the intra-sequence and inter-sequence feature representation of videos, and outputs self-and-collaborative feature representation for each video, making the discriminative frames aligned between the probe and gallery sequences. Second, beyond existing models, a generalized pairwise similarity measurement is proposed to calculate the similarity feature representations of video pairs, enabling computing the matching scores by the binary classifier. Third, a dense clip segmentation strategy is also introduced to generate rich probe-gallery pairs to optimize the model. Extensive experiments demonstrate the effectiveness of SCAN, which outperforms top-1 accuracies of the best-performing baselines by 7.8%, 2.1% and 4.9% on iLIDS-VID, PRID2011 and MARS dataset, respectively.

1. Introduction

As one of the core problems in intelligent surveillance and multimedia application, person re-identification attracts much attention in literature [47, 20, 26, 43, 5, 16]. It aims to re-identify individual persons across non-overlapping cameras distributed at different physical locations. In practice, dramatic appearance changes caused by illumination, occlusions, viewpoint and background clutter increases the difficulty of re-id task. A lot of work have been proposed to deal with these problem in still images [47, 20, 26, 43, 5, 16]. Beyond this, there also exist several studies [25, 38, 50, 40] discussing the re-id task under image sequence (video) setting. Since an image sequence usually contains rich temporal information, it is more suitable to identify a person under complex environment and large geometric variations.

As shown in Fig.1, besides extracting the feature representation of each frame by convolutional neural networks (CNN), existing deep video re-identification methods usu-
Attention Network (SCAN) to jointly deal with frame sample but effective architecture termed Self-and-Collaborative Sequence or the feature dimension of frames need to be fixed. are usually parametric, making the length of the input sequence for the attention mechanism to discover discriminative features and loss functions in previous studies are not suitable. Second, some combinations of similarity measures and loss functions in previous studies are not suitable for the attention mechanism to discover discriminative frames. Third, the attention mechanism in existing methods are usually parametric, making the length of the input sequence or the feature dimension of frames need to be fixed.

In order to address the above issues, we propose a simple but effective architecture termed Self-and-Collaborative Attention Network (SCAN) to jointly deal with frame selection, temporal pooling and similarity measurement for video re-identification task. As shown in Table 1, it has several benefits that existing methods do not have. a) Compared with the recurrent neural network (RNN) based attention network, SCAN adopts attention mechanism to refine the intra-sequence and inter-sequence feature representation of sequences. Such process can efficiently align discriminative frames between the probe and gallery image sequences. The output self and collaborative feature representations leverage the global temporal information and local discriminative information. b) We propose a generalized pairwise similarity measurement in SCAN, which adopts self and collaborative video representations to calculate the similarity features of video pairs. Thus the matching problem can be transformed into a binary classification problem, and the label of an identity pair is used to optimize the classifier. Such module encourages the video features from the same identity to be similar, and enlarges the distance between informative frames and noisy frames in the same video. Moreover, different from pair-wise loss or triplet loss that needs a predefined margin constraint [6], the binary loss can reduce the cost to tune such hyperparameter. c) The attention module in SCAN is non-parametric, thus it can deal with image sequence with various lengths and the input feature dimensions of each frame is also variable. d) A dense clip segmentation strategy is introduced to generate much more probe-gallery pairs (including the hard positive and hard negative pairs) to optimize the model.

As shown on the right of Fig.1, in practice, we first extract the feature representation of each frame (green circles) from both probe and gallery videos using pre-trained CNN. Then the sequence representation (green rectangle) is calculated by average pooling according to the temporal domain. After feature extraction, we input the frame-level and sequence-level features from the probe and gallery videos into self attention subnetwork (SAN) independently. After calculating the correlation (the attention weight) between the sequence and its frames, the output sequence representation is reconstructed as a weighted sum of the frames at different temporal positions in the input sequence. The red arrow in Fig.1 denotes these two steps. We also introduce the collaborative attention subnetwork (CAN) to calculate the coupled feature representations of the input sequence pair. The calculation process of CAN is the same as the SAN, but the meaning of the output various according to different inputs. For instance, if the input sequence-level feature is from the probe video and the frame-level features are from the gallery video, the output of CAN will be the probe-driven gallery representation. Otherwise, it will be the gallery-driven probe representation. After SAN and CAN, we calculate the difference between self-representations of the probe and gallery videos, as well as the difference between their collaborative-representations. These two differ-

| Method         | Frame | P-G | Var. | P-G |
|----------------|-------|-----|------|-----|
| Mc. et al. [25] | ✓     | ✓   | ✓    | ✓   |
| Zhou et al. [50]| ✓     | ✓   | ✓    |     |
| Xu et al. [40]  | ✓     | ✓   | ✓    | ✓   |
| Liu et al. [24] | ✓     | ✓   | ✓    | ✓   |
| Li et al. [17]  | ✓     | ✓   | ✓    | ✓   |
| our method      | ✓     | ✓   | ✓    | ✓   |

Table 1: The proposed SCAN integrates the benefits of the previous work into a unique framework, and also introduces some elaborate mechanisms to further improve the performance of video re-id. ‘Frame Align.’, ‘P-G Inter.’, ‘Var. Dim.’ and ‘P-G Pair Aug.’ are short for frame alignment, probe-and-gallery interaction, accepting temporal modeling with various feature dimensions (i.e. various number of frames and channels) and probe-and-gallery pair augmentation.
In general, the contribution of this work can be summarized in three folds. (1) We propose a Self-and-Collaborative Attention Network (SCAN) to efficiently align the discriminative frames from two videos. It includes a non-parametric attention module to generate self and collaborative sequence representations by refining intra-sequence and inter-sequence features of input videos. A generalized pairwise similarity measurement is also adopted to calculate the similarity feature representations of video pairs. (2) We introduce such a module into video re-identification task, and propose a novel and practical framework to simultaneously deal with frame selection, video temporal representation and similarity measurement. In addition, a dense clip segmentation strategy is also introduced to generate much more probe-gallery pairs to optimize the model. (3) The proposed model outperforms the state-of-the-art methods with a large margin on three standard video re-identification benchmarks.

### 2. Related Work

**Person re-identification.** Person re-id in still image has been extensively explored in the literature [47, 20, 26, 21, 43, 5, 16] in the past few years. Recently, the studies about video-based person re-identification employ image sequence to further improve the matching accuracy [25, 45, 38, 50, 7, 40]. For example, McLaughlin et al. [25] proposed a basic pipeline for deep video re-id. It uses CNN to extract the feature of each frame. Then the RNN layer is applied to incorporate temporal context information into each frame, and the temporal pooling operation is adopted to obtain the final sequence representation. Both the identity loss and siamese loss are used to optimize parameters. In [38], Wu et al. proposed a similar architecture to jointly optimize CNN and RNN to extract the spatial-temporal feature representation for similarity measurement. In recent studies, one of the remarkable property is applying the attention mechanism to discover the discriminative frames from probe and gallery videos. As shown in Table 2, Zhou et al. [50] proposed a temporal attention mechanism to pick out the discriminative frames for video representation. Moreover, the spatial RNN is adopted to integrate the context information from six directions to enhance the representation of each location in the feature maps. Li et al. [17] proposed a spatio-temporal attention model and diversity regularization to discover a set of distinctive body parts for the final video representation. In [40], Xu et al. introduced the shared attention matrix for temporal modeling, realizing the information exchange between probe and gallery sequence in the process of frame selection. In such case, the discriminative frames can be aligned according to their attention weights. Our method is partially related to this work. Since the proposed SCAN outputs the attention weights by leveraging global temporal information and local discriminative information, it is more robust to deal with the noise frames during alignment. On the other hand, it is a non-parametric module, thus can be more flexible to deal with sequences with various length. In [48] Zhong et al. also take the probe-and-gallery interaction into consideration to further improve the retrieval accuracy. However, such interaction is exploited in the re-ranking stage, and the attention mechanism is also omitted.

**Self-attention and interaction network.** Recent developed self-attention [30] mechanism for machine translation is also related to our work. It calculated the response at one position as a weighted sum of all positions in the sentence. The similarity idea was also introduced in Interaction Networks (IN) [2, 35, 14] for modeling the pairwise interactions in physical systems. Recently, Wang et

| Method          | Spatial Info. | Temporal Modeling | P-G. Inter. | Loss Func. | Identity Loss | Video Clips |
|-----------------|---------------|--------------------|-------------|------------|---------------|-------------|
| Mc. et al. [25] | ✓              | RNN + pooling      | ✓           | P          | ✓             | cons.       |
| Zhou et al. [50]| ✓             | LSTM + attention + pooling | ✓           | T, B       | ✓             | rand.       |
| Xu et al. [40]  | ✓             | RNN + attention + pooling | ✓           | P          | ✓             | cons.       |
| Liu et al. [24] | ✓             | weighted sum       | ✓           | T          | ✓             | cons.       |
| Zhong et al. [48]| ✓             | max pooling        | ✓           | P          | ✓             | rand.       |
| Li et al. [17]  | ✓             | weighted sum       | ✓           | –          | ✓             | dense       |

Table 2: Comparisons between proposed SCAN and other state-of-the-arts for video person re-id. ✓ represents the methods or information indicated by the column indices are adopted. ‘non-para.’ is short for non-parametrization in temporal modeling, and ‘P-G. Inter.’ for probe-galley interaction during sequence representation generation. The uppercase ‘P’, ‘T’ and ‘B’ in the sixth column indicate pairwise loss, triplet loss and binary loss, respectively. In the last column, ‘cons.’ denotes the clip of each video is extracted from consecutive frames, and ‘rand.’ means randomly extracting several frames from the video as the clip. The ‘dense’ indicates our model segment the image sequence into multiple clips for model training.
al. [33] extended these methods into computer vision area, and proposed the Non-Local Network to model the long-range spatial and temporal dependencies in a single block. In [49], Zhou et al. proposed the Temporal Relation Network (TRN) to learn temporal dependencies between video frames at multiple time scales. The proposed SCAN is inspired by above two works, but we further introduce the collaborative representation mechanism to deal with the matching problem.

**Collaborative representation.** Learning collaborative representation aims to represent a sample as a weighted linear combination of all training samples. It has been successfully applied in many computer vision tasks, such as face recognition [37, 44], super-resolution [27], image denoising [4] and so on. In this paper, we introduce a collaborative representation into temporal modeling, and combine it with deep neural networks for end-to-end training. Specifically, self and collaborative attention network are proposed to represent the video as a weighted combination of multiple frames.

**Similarity learning.** Learning the similarity metric is a natural solution for matching problem. Traditional metric learning methods [10, 36, 8, 41] usually learned a common space for visual data from different domains. Instead of using hand-craft feature, many work [19, 1, 34, 22] integrated the feature learning and metric learning into deep neural networks. Our model is partially motivated by the above work. However, the proposed SCAN aims to incorporate a parameter free similarity function into deep models to align the discriminative frames in probe and gallery videos.

3. Methodology

In this section, we first present the deep architecture of proposed model in Sec. 3.1. Then the connection between our method and traditional metric learning are presented in Sec. 3.2. Sec. 3.3 gives more implementation details about the proposed method.

3.1. Deep Architecture

**Feature extraction.** The deep architecture of proposed method is illustrated in Fig. 2. Supposing the probe image sequence is represented as \( I_b = \{ I_{b,t} \}_{t=1}^{T} \) and the gallery sequence is as \( I_g = \{ I_{g,t} \}_{t=1}^{R} \). \( T \) and \( R \) indicate the length of the image sequences. The probe and gallery sequences are at first fed into CNN to extract the feature representation of each frame. The parameters of CNN are shared for both sequences. Let the feature representation of the probe and gallery video be \( X = \{ x^t | x^t \in \mathbb{R}^d \}_{t=1}^{T} \) and \( Y = \{ y^r | y^r \in \mathbb{R}^d \}_{r=1}^{R} \), where \( d \) is the dimension of the feature vector and \( T \) is set as 2048 in practice. We further apply the fc-0 layer to reduce the feature dimension to 128 and denote them as \( X_f = \{ x_{f,t} \}_{t=1}^{T} \) and \( Y_f = \{ y_{f,r} \}_{r=1}^{R} \), respectively.

**Self Attention Subnetwork.** After feature extraction, the Self Attention Network (SAN) is adopted to select the informative frames to further enhance the representation of each image sequence. We first feed \( \{ X, X_f \} \) and \( \{ Y, Y_f \} \) into SAN. Then the dimension of \( X \) and \( Y \) is reduced from 2048 to 128 using fc-1 layer and denoted as \( X_s = \{ x_{s,t} \}_{t=1}^{T} \) and \( Y_s = \{ y_{s,r} \}_{r=1}^{R} \). After that, the sequence-level representation of \( X_s \) and \( Y_s \) are produced through average pooling over the temporal dimension. Let \( x_s \) and \( y_s \) be the sequence-level feature vector of probe and gallery video in

Figure 2: Architecture of proposed Self-and-Collaborative Attention Network. This architecture is comprised of four parts: shared convolutional neural networks, self attention subnetwork (SAN), collaborative attention subnetwork (CAN) and similarity measurement module. The video clips from probe and gallery image sequences are first fed into CNN to obtain frame-level features. Then SAN and CAN are adopted to generate video-level representation according to the non-parametric attention mechanism. At last, the binary cross-entropy loss and identity loss are used to optimize the parameters of SCAN. Zoom in four times for best view.
SAN, we further enhance these feature representations by,
\[
\hat{x}_{xx} = \sum_{t=1}^{T} f(x^t_x, \hat{x}_x) \circ x^f_t \quad \hat{y}_{yy} = \sum_{r=1}^{R} f(y^r_y, \hat{y}_y) \circ y^f_r \tag{1}
\]
where \( f(\cdot, \cdot) \) is a parameter-free correlation function, which outputs the correlation weight of input features. It may have various forms [33]. In this paper, we adopt Hadamard product to calculate the correlation weight, thus the output of \( f(\cdot, \cdot) \) is the correlation weight vector and \( \circ \) indicates the Hadamard product. The softmax operation along the temporal dimension (\( t \) and \( r \)) is also used for normalizing these weights. The subscript \( xx \) indicates the probe-driven probe representation, while \( yy \) indicates the gallery-driven gallery representation. The output \( \hat{x}_{xx} \) and \( \hat{y}_{yy} \) are then passed into collaborative attention subnetwork.

**Collaborative Attention Subnetwork.** The input of CAN is from two branches. One is the sequence-level representation \( \hat{x}_{xx} \) and \( \hat{y}_{yy} \) from SAN, and the other is the frame-level representations \( \{X, X_f\} \) and \( \{Y, Y_f\} \) from CNN. Same as SAN, we reduce the dimension of \( X \) and \( Y \) from 2048 to 128 using fc-2 layer in CAN. The outputs are \( X_c = \{x^t_c\}_{t=1}^{T} \) and \( Y_c = \{y^r_c\}_{r=1}^{R} \). Then the cross-camera feature representation can be computed as,
\[
\hat{x}_{xy} = \sum_{t=1}^{T} f(x^t_x, \hat{y}_{yy}) \circ x^f_t \quad \hat{y}_{xy} = \sum_{r=1}^{R} f(y^r_y, \hat{x}_{xx}) \circ y^f_r \tag{2}
\]
The subscript \( xy \) indicates the probe driven gallery representation, and \( gx \) is the gallery driven probe representation. The operation in Eqn.(2) enables probe and gallery video to effectively select discriminative frames from each other.

**Similarity measurement.** We use the output of SAN and CAN to calculate the similarity feature representation between probe sequence and gallery sequence as follows,
\[
s = (\hat{x}_{xx} - \hat{y}_{yy}) \circ (\hat{x}_{xy} - \hat{y}_{xy}) \\
= (\hat{x}_{xx} \circ \hat{x}_{xy} - \hat{y}_{yy} \circ \hat{y}_{xy}) + (\hat{x}_{xy} \circ \hat{y}_{yy} - \hat{x}_{xx} \circ \hat{y}_{xy}) \\
= (X_f \cdot \hat{c}_{xx} \circ X_f \cdot \hat{c}_{xy}) - (Y_f \cdot \hat{c}_{yy} \circ Y_f \cdot \hat{c}_{xy}) + (Y_f \cdot \hat{c}_{yy} \circ X_f \cdot \hat{c}_{xy}) - (X_f \cdot \hat{c}_{xx} \circ Y_f \cdot \hat{c}_{xy}) 	ag{3}
\]
where \( \hat{c}_{xx}, \hat{c}_{yy}, \hat{c}_{xy}, \hat{c}_{yx} \) denotes the combination coefficient matrices calculated by the non-parameter correlation function \( f(\cdot, \cdot) \). The meaning of subscripts are consistent with that in the sequence-level representation. The operation \( \circ \) indicates weighted combination along each feature dimension, and \( \circ \) denotes the Hadamard product. Note that \( s \) is a vector but not a scalar, which indicates the sequence-level similarity after frame selection. This feature representation is then transformed by a fully-connected layer, i.e. fc-3 layer, to obtain the final matching score. At last, we adopt identity pair annotation and binary cross-entropy loss to optimize the matching score,
\[
\mathcal{L} = -\frac{1}{N} \sum_{i=1}^{N} \left[ l_i \log m_i + (1 - l_i) \log (1 - m_i) \right] \tag{4}
\]
where \( N \) is the number of probe-gallery pairs in the training set, \( m_i \) is the predicted matching score of \( i \)-th pair, and \( l_i \) indicates its label. If the probe video and gallery video present the same person identity, the value of \( l_i \) is 1, else it will be 0. The same operation is also used in textual-visual matching problem [18].

### 3.2. Compared with Traditional Metric Learning

According to [22], the generalized linear similarity of two feature vectors can be written as,
\[
\tilde{s} = [x^T \ y^T] \begin{bmatrix} A & -C \\ -D & B \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \\
= (x^T A x - y^T D x) + (y^T B y - x^T C y) \\
= (\{A x_f \hat{c}_{xx} - \{D y_f \hat{c}_{xy} \}^T D x_f \hat{c}_{xy}) + (\{B y_f \hat{c}_{yy} - \{C x_f \hat{c}_{xy} \})^T C y_f \hat{c}_{xy} 
\]
Part A
\[
\begin{bmatrix} \tilde{s} - (x^T \ y^T)M(x \ y) \end{bmatrix} 
\] Part B
\[
\text{where } A, B, C, \text{ and } D \text{ are the parameters to be optimized, and } \\
A = A \ A, B = B \ B, C = C_y \ C_y \text{ and } D = D_y \ D_x. \\
\text{We have } A = B = C = M \text{ and } D = M^T, \text{ it degenerates into Mahalanobis distance with the form } \tilde{s} = (x - y)^T M (x - y). \text{ Intuitively, Eqn.(3) has a very similar form with Eqn.(5). The differences are three folds: First, we replace } \begin{bmatrix} A & -C \\ -D & B \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \text{ with two sets of frame-level feature representations } X_f \text{ and } Y_f, \text{ respectively. Second, we rewrite feature vector } x \text{ and } y \text{ as the linear combination coefficients } c. \text{ computed by correlation function } f(\cdot, \cdot), \text{ which uses sequence-level feature representation as anchors to calculate the correlation weights between frame-level features and the corresponding sequence-level features. At last, some dot product operations are replaced by element-wise product.}

In fact, our method adopts the temporal attention mechanism to project two image sequences into a compact 'frame
3.3. Implementation Details

Clip Segmentation. In practice, we segment every image sequence into several video clips. The length of each clip is 2048 and the segmentation stride is set as 5 in training and test procedure. When the frames at the end of the video are not sufficient to generate the clip, we discard the rest frames directly. The advantage of such pre-processing strategy are as follows: (a) It can generate a large amount of probe-gallery pairs to optimize network parameters, which is critical for the deep model training. Specially, it is beneficial to produce much more hard positive/negative training pairs to promote the training efficiency. (b) It avoids loading the entire image sequence into the model for temporal modeling. In such case, when the batch size is fixed, it can increase the diversity of minibatch effectively. This ensures the training process more stable and BatchNorm (BN) [15] more efficient to accelerate the model convergence. In the test phase, we select 20 snippet pairs with the highest matching score from coupled image sequences and average these 20 matching scores as the final confidence score. We rank all of the confidence scores and return the final ranking list to calculate the matching accuracy.

Training process. The architecture of proposed SCAN is shown in Table 3. All of the CNN models in this work are pre-trained on ImageNet [9]. We fine-tune the models using 16 identities in each batch. Each person corresponds to 2 video snippets. In summary, there are 32 clips with 320 video frames as the input for each iteration. The input frames are resized into 256 × 128 pixels. Horizontal flipping is also used for data augmentation. We adopt Online Instance Matching (OIM) [39] loss as the identity loss function. We train our models on 4-GPU machine. Each model is optimized 30 epochs in total, and the initial learning rate is set as 0.001. The learning rate is updated with the form, \( lr = lr_0 \times 0.001^{(epoch/10)} \), where \( lr_0 \) denotes the initial learning rate. We use a momentum of 0.9 and a weight decay of 0.0001. The parameters in BN layers are also updated in the training phase.

| Name   | Layer     | Output Size   |
|--------|-----------|---------------|
| conv1  | 7 × 7, 64, stride 2 | 2 × 10 × 128 × 64 |
| pool1  | 3 × 3, max pool, stride 2 | 2 × 10 × 64 × 64 |
| res2   | [3 × 3, 64] × 3 | 2 × 10 × 64 × 32 |
| res3   | [3 × 3, 128] × 4 | 2 × 10 × 32 × 26 |
| res4   | [3 × 3, 256] × 6 | 2 × 10 × 16 × 8 |
| res5   | [3 × 3, 512] × 3 | 2 × 10 × 8 × 4  |
| pool5  | average pool | 2 × 10 × 1 × 2048 |
| fc0    | 2048 × 128 | 2 × 10 × 1 × 128 |

Table 3: The architecture of proposed SCAN. The basic model is ResNet50 [11]. The dimensions of the output indicate the number of the clips, the number of the frames in each clip, the height and width of feature maps and the number of channels, respectively. The optical flow is omitted.

space’ to align the discriminative frames in the probe and gallery videos, and use these discriminative frames to generate the final representations of the videos. It is essentially different between our method and previous metric learning work, which projects the data into a common feature space by using linear transformations and output the distance to indicate the matching score. That is also the reason that the output of Eqn.(3) is a similarity feature vector of two image sequences but not a distance. In this sense, our work bridges the metric learning for feature projection with the temporal frame selection, which is a common technique in a series of video-based applications.

4. Experiments

We have conducted extensive experiments to clarify the superiority of proposed method. In this section, the experimental setting, experimental results and ablation analysis are presented in Sec. 4.1, Sec. 4.2 and Sec. 4.3.

4.1. Experimental Setting

Datasets: We evaluate the performance of proposed method on three well known video re-identification benchmarks: the iLIDS-VID dataset [32], the PRID 2011 dataset [13] and the MARS dataset [45]. (a) iLIDS-VID contains 600 image sequences of 300 pedestrians under two cameras. Each image sequence has 23 to 192 frames. Both of the training and test set have 150 identities. (b) PRID is another standard benchmark for video re-identification. It consists of 300 identities and each has 2 image sequences. The length of sequences varies from
Table 4: Performance comparison on the iLIDS-VID by state-of-the-art methods. Our model is based on ResNet50. Top-1, -5, -10, -20 accuracies(%) are reported.

5 to 675. (c) MARS is one of the largest video person re-identification dataset which contains 1,261 different pedestrians and 20,715 tracklets captured from 6 cameras. In this dataset, each person has one probe under each camera, resulting in 2,009 probes in total. The dataset is divided into training and test sets that contains 631 and 630 persons respectively.

**Evaluation Metric:** Two widely used evaluation metrics are used for comparison. The first is the cumulative matching characteristic (CMC) [3], which considers re-id as the ranking problem. Since the tracklets in MARS dataset are captured from 6 camera, the ranking list may contain multiple matching results. Thus we also adopt mean average precision (mAP) [46] to evaluate the performance in this dataset. In this case, the re-id problem is regarded as the retrieval problem.

**Optical Flow:** For fair comparison and further improving the performance of video re-id, we use the optical flow [31, 28] to extract the motion information from image sequence. In practice, the dimension of input optical flow for each frame is $2 \times H \times W$, where 2 denotes the number of vertical and horizontal channels. $H$ and $W$ indicate the height and width of the map. The value range of optical flow is scaled to 0 to 255. Through one convolution layer (with BN and ReLU operation) and one pooling layer, the dimension of feature maps in optical branch becomes $64 \times \frac{1}{4} H \times \frac{1}{4} W$, which is same as RGB branch. Then an element-wise addition is applied to merge these two modalities, and the outputs are fed into the rest layers. Fig. 3 illustrates the operation.

### 4.2. Comparison with State-of-the-arts

We firstly report the comparison of proposed method with existing eleven state-of-the-art video person re-identification methods on iLIDS-VID dataset and PRID2011 dataset, including LFDA [26], LADF [20], STFV3D [23], TDL [42], CNN-RNN [25], CNN+XQDA [45], TAM+SRM [50], ASTPN [40], QAN [24], RQEN [29] and STAN [17]. The first four methods are traditional methods without using deep models, while the others adopt deep neural networks to extract the feature representation of each frame. We use ResNet50 [11] as the basic model of proposed SCAN. Following [40], each dataset is randomly split into 50% of identities for training and others for testing. All experiments are repeated 10 times with different train/test splits, and the averaged results are reported. As shown in Table 4 and Table 5, our method achieves state of the art 88.0% and 95.3% top-1 accuracy on iLIDS-VID and PRID2011, outperforming the existing best method STAN [17] with 7.8% and 2.1%, respectively.

To further demonstrate the effectiveness of SCAN on the data captured from multiple camera views, we compare it with state-of-the-arts on MARS dataset, including CNN+Kissme+MQ [45], Latent Parts [16], TAM+SRM [50], QAN [24], K-Recip. [48], TriNet [12], RQEN [29] and STAN [17]. Table 6 reports the retrieval results. Our approach outperforms previous state-of-the-arts on top-1 accuracy and mAP, and obtains 4.9% and 11.4% improvement.

### 4.3. Ablation Study

To investigate the efficacy of proposed SCAN, we conduct ablation experiments on iLIDS-VID, PRID2011 and
Table 5: Performance comparison on the PRID2011 by state-of-the-art methods. Our model is based on ResNet50. Top-1, -5, -10, -20 accuracies(%) are reported.

| Methods          | Source  | Deep model | PRID2011 |
|------------------|---------|------------|----------|
|                  |         |            | top-1    | top-5    | top-10   | top-20   |
| 1. LFDA [26]     | cvpr13  | no         | 43.7     | 72.8     | 81.7     | 90.9     |
| 2. LADF [20]     | cvpr13  | no         | 47.3     | 75.5     | 82.7     | 91.1     |
| 3. STFV3D [23]   | iccv15  | no         | 64.7     | 87.3     | 89.9     | 92.0     |
| 4. TDL [42]      | cvpr16  | no         | 56.7     | 80.0     | 87.6     | 93.6     |
| 5. CNN-RNN [25]  | cvpr16  | yes        | 70.0     | 90.0     | 95.0     | 97.0     |
| 6. CNN+XQDA [45] | eccv16  | yes        | 77.3     | 93.5     | –        | 99.3     |
| 7. TAM+SRM [50]  | cvpr17  | yes        | 79.4     | 94.4     | –        | 99.3     |
| 8. ASTPN [40]    | iccv17  | yes        | 77.0     | 95.0     | 99.0     | 99.0     |
| 9. QAN [24]      | cvpr17  | yes        | 90.3     | 98.2     | 99.3     | 100.0    |
| 10. RQEN [29]    | aaai18  | yes        | 91.8     | 98.4     | 99.3     | 99.8     |
| 11. STAN [17]    | cvpr18  | yes        | 93.2     | –        | –        | –        |
| 12. ours w/o optical | –     | yes    | 92.0     | 98.0 | 100.0 | 100.0 |
| 13. ours w/ optical | –     | yes    | 95.3     | 99.0     | 100.0    | 100.0    |

Table 6: Performance comparison on the MARS by state-of-the-art methods. Our model is based on ResNet50. Top-1, -5, -20 accuracies(%) and mAP(%) are reported.

| Methods           | Source  | Deep model | MARS    |
|-------------------|---------|------------|---------|
|                   |         |            | top-1   | top-5   | top-20  | mAP    |
| 1. CNN+Kiss.+MQ   | eccv16  | yes        | 68.3    | 82.6    | 89.4    | 49.3   |
| 2. Latent Parts   | cvpr17  | yes        | 71.8    | 86.6    | 93.0    | 56.1   |
| 3. TAM+SRM        | cvpr17  | yes        | 70.6    | 90.0    | 97.6    | 50.7   |
| 4. QAN            | cvpr17  | yes        | 73.7    | 84.9    | 91.6    | 51.7   |
| 5. K-reciprocal   | cvpr17  | yes        | 73.9    | –       | –       | 68.5   |
| 6. TriNet         | arxiv17 | yes        | 79.8    | 91.4    | –       | 67.7   |
| 7. RQEN           | aaai18  | yes        | 77.8    | 88.8    | 94.3    | 71.1   |
| 8. STAN           | cvpr18  | yes        | 82.3    | –       | –       | 65.8   |
| 9. ours w/o optical | –     | yes    | 86.6    | 94.8    | 97.1    | 76.7   |
| 10. ours w/ optical | –     | yes    | 87.2    | 95.2    | 98.1    | 77.2   |

MARS dataset. The average pooling over temporal dimension is used to be our baseline model if not specified. The overall results are shown on Table 7. We also consider the impact of the cutting length of video clips. The comparison results are shown in Table 8.

**Instantiations.** We compared our full model with five simplified settings, including (1) using the average pooling over temporal dimension to calculate the feature representation of both the probe and gallery sequences; (2) using max pooling to replace average pooling in (1); (3) using Self Attention Network (SAN) to compute probe and gallery video features separately; (4) using average pooling to obtain the video-level feature representation firstly, and using Collaborative Attention Network (CAN) to reconstruct probe and gallery video representations; (5) using SAN to calculate probe video feature, followed by employing such feature representation to reconstruct gallery video representation by CAN. This setting can be viewed as a single-path variant of the proposed SCAN. For all of the above methods, we adopt the difference between two obtained video features as the similarity representation, and apply loss function in Eqn. 4 for optimization.

According to Table 7, we have several important findings. First, the baseline model (i.e. ave. pooling) has already outperformed state-of-the-art methods with a margin. It demonstrates the effectiveness of proposed pipeline, including clip segmentation and binary cross-entropy loss in Eqn.(4). Second, the matching accuracy achieves a slight improvement when only using SAN or CAN for temporal modeling, but single path SCAN outperforms the baseline with a margin. It suggests that the SAN and CAN modules are coupled when aligning the discriminative frames in the probe and gallery image sequences. At last, the performance of the single-path SCAN is less than our...
full model, reflecting the importance of generalized similarity representation between probe and gallery sequences in the matching problem.

**Video clip with different length.** We also investigate the performance of the SCAN model using different length of video clips. We cut the input image sequence into several clips with 10 frames, 16 frames and 20 frames, and the number of overlapped frames (i.e., the stride of the sliding window over the temporal dimension) is set as 5, 8 and 10, respectively. In Table 8, the setting with 10 frames achieves the best performance over all of the evaluation metrics. We can also observe that as the clip length grows, the accuracy drops gradually. It demonstrates the cutting strategy can provide more diverse pairs in the minibatch, which increases the model capacity effectively.

### 5. Conclusions

In this paper, we propose a novel Self-and-Collaborative Attention Network for video person re-identification, which integrates frame selection, temporal pooling and similarity measurement into a simple but effective module. Different from traditional metric learning method that project the video-level representations into a common feature space for similarity measurement, SCAN adopts the proposed generalized similarity measurement to align two image sequences in the ‘frame space’, and generates the final representation with the selected discriminative frames. Extensive experiments demonstrate the proposed SCAN outperforms the state-of-the-art methods.

Several directions can be considered to further improve our model. First, extending SCAN into the spatial-temporal dimension is an intuitive idea. Second, how to efficiently integrate the multi-modality information, e.g., RGB and optical flow, into a single framework is still an open issue. At last, combining proposed method with other visual tasks, such as video object detection or video-based instance segmentation, is also an exciting research direction.

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