Learning Person Re-identification Models from Videos with Weak Supervision

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Abstract—Most person re-identification methods, being supervised techniques, suffer from the burden of massive annotation requirement. Unsupervised methods overcome this need for labeled data, but perform poorly compared to the supervised alternatives. In order to cope with this issue, we introduce the problem of learning person re-identification models from videos with weak supervision. The weak nature of the supervision arises from the requirement of video-level labels, i.e. person identities who appear in the video, in contrast to the more precise frame-level annotations. Towards this goal, we propose a multiple instance attention learning framework for person re-identification using such video-level labels. Specifically, we first cast the video person re-identification task into a multiple instance learning setting, in which person images in a video are collected into a bag. The relations between videos with similar labels can be utilized to identify persons, on top of that, we introduce a co-person attention mechanism which mines the similarity correlations between videos with person identities in common. The attention weights are obtained based on all person images instead of person tracklets in a video, making our learned model less affected by noisy annotations. Extensive experiments demonstrate the superiority of the proposed method over the related methods on two weakly labeled person re-identification datasets.

Index Terms—Video person re-identification, Weak supervision, Co-person attention mechanism

I. INTRODUCTION

PERSON re-identification (re-id) is a cross-camera instance retrieval problem which aims at searching for persons across multiple non-overlapping cameras [1], [2], [3], [4], [5], [6], [7], [8]. This problem has attracted extensive research, but most of the existing works focus on supervised learning approaches [2], [9], [10], [11], [12]. While these techniques are extremely effective, they require a substantial amount of annotations which becomes infeasible to obtain for large camera networks. Aiming to reduce this huge requirement of labeled data, unsupervised methods have drawn a great deal of attention [13], [14], [15], [16], [17], [18], [19]. However, the performance of these methods is significantly weaker compared to supervised alternatives, as the absence of labels makes it extremely challenging to learn a generalizable model.

To bridge this gap in performance, some recent works have focused on the broad area of learning with limited labels. This includes settings such as the one-shot, the active learning and the intra-camera labeling scenarios. The one-shot setting [18], [19], [20], [21] assumes a singular labeled tracklet for each identity along with a large pool of unlabeled tracklets, the active learning strategy [22], [23], [24] tries to select the most informative instances for annotation, and the intra-camera setting [25], [26] works with labels which are provided only for tracklets within an individual camera view. All of these methods assume smaller proportions of labeling in contrast to the fully supervised setting, but assume strong labeling in the form of identity labels similar to the supervised scenario. In this paper, we focus on the problem of learning with weak labels - labels which are obtained at a higher level of abstraction, at a much lower cost compared to strong labels. In the context of video person re-id, weak labels correspond to video-level labels instead of the more specific labels for each image/tracklet within a video.

To illustrate this further, consider Figure 1 which shows some video clips which are annotated with the video-level...
labels, such as video 1 with \{A, B, C, D, E\}. This indicates that Person A, B, C, D and E appear in this clip. By using pedestrian detection and tracking algorithms [27], [28], [29], we can obtain the person images (tracklets) for this video clip, but can make no direct correspondence between each image (tracklet) and identity due to the weak nature of our labels. Specifically, we group all person images obtained in one video clip into a bag and tag it with the video label as shown in Figure 1(c). On the contrary, strong supervision requires identity labels for each image (tracklet) in a video clip and thus, annotation is a more tedious procedure compared to our setting. Thus, in weakly labeled person re-id data, we are given bags, with each such bag containing all person images in a video and the video’s label; our goal is to train a person re-id model using these bags which can perform retrieval during test time at two different levels of granularity. The first level of granularity, which we define as Coarse-Grained Re-id, involves retrieving the videos (bags) that a given target person appears in. The second level entails finding the exact tracklets with the same identity as the target person in all obtained gallery tracklets - this is defined as Fine-Grained Re-id. Moreover, we also consider a more practical scenario where the weak labels are not reliable - the annotators may not tag the video clip accurately.

In order to achieve this goal, we propose a multiple instance attention learning framework for video person re-id which utilizes pairwise bag similarity constraints via a novel co-person attention mechanism. Specifically, we first cast the video person re-id task into a multiple instance learning (MIL) problem which is a general idea that used to solve weakly-supervised problems [31], [32], however, in this paper, a novel \(k\)-max-mean-pooling strategy is used to obtain a probability mass function over all person identities for each bag and the cross-entropy between the estimated distribution and the ground truth identity labels for each bag is calculated to optimize our model. The MIL considers each bag in isolation and does not consider the correlations between bags. We address this by introducing the Co-Person Attention Loss (CPAL), which is based on the motivation that a pair of bags having at least one person identity e.g. Person A in common should have similar features for images which correspond to that identity (A). Also, the features from one bag corresponding to A should be different from features of the other bag (of the pair) not corresponding to A. We jointly minimize these two complementary loss functions to learn our multiple instance attention learning framework for video person re-id as shown in Figure 2.

To the best of our knowledge, this is the first work in video person re-id which solely utilizes the concept of weak supervision. A recent work [5] presents a weakly supervised framework to learn re-id models from videos. However, they require strong labels, one for each identity, in addition to the weak labels, resulting in a semi-weak supervision setting. In contrast, our setting is much more practical forgoing the need for any strong supervision. A more detailed discussion on this matter is presented in Section IV-E where we empirically evaluate the dependence of [5] on the strong labels and demonstrate the superior performance of our framework.

Main contributions. The contributions of our work are as follows:

- We introduce the problem of learning a re-id model from videos with weakly labeled data and propose a multiple instance attention learning framework to address this task.
- By exploiting the underlying characteristics of weakly labeled person re-id data, we present a new co-person attention mechanism to utilize the similarity relationships...
between videos with common person identities.

- We conduct extensive experiments on two weakly labeled datasets and demonstrate the superiority of our method on coarse and fine-grained person re-id tasks. We also validate that the proposed method is promising even when the weak labels are not reliable.

II. RELATED WORKS

Existing person re-id works can be summarized into three categories, such as learning from strongly labeled data (supervised and semi-supervised), learning from unlabeled data (unsupervised) and learning from weakly labeled data (weakly supervised) depending on the level of supervision. This section briefly reviews some person re-id works, which are related with this work.

Learning from strongly labeled data. Most studies for person re-id are supervised learning-based methods and require the fully labeled data [31], [10], [2], [9], [11], [32], [33], i.e., the identity labels of all the images/tracklets from multiple cross-view cameras. These fully supervised methods have led to impressive progress in the field of re-id; however, it is impractical to annotate very large-scale surveillance videos due to the dramatically increasing annotation cost.

To reduce annotation cost, some recent works have focused on the broad area of learning with limited labels, such as the one-shot settings [18], [19], [20], [21], the active learning strategy [22], [23], [24] and the intra-camera labeling scenarios [25], [26]. All of these methods assume smaller proportions of labeling in contrast to the fully supervised setting, but assume strong labeling in the form of identity labels similar to the supervised scenario.

Learning from unlabeled data. Researchers developed some unsupervised learning-based person re-id models [12], [13], [14], [15], [16], [17] that do not require any person identity information. Most of these methods follow a similar principle - alternatively assigning pseudo labels to unlabeled data with high confidence and updating model using these pseudo-labeled data. It is easy to adapt this procedure to large-scale person re-id task since the unlabeled data can be captured automatically by camera networks. However, most of these approaches perform weaker than those supervised alternatives due to lacking the efficient supervision.

Learning from weakly labeled data. The problem of learning from weakly labeled data has been addressed in several computer vision tasks, including object detection [34], [35], [36], segmentation [36], [37], text and video moment retrieval [38], activity classification and localization [39], [40], [41], video captioning [42] and summarization [43], [44]. There are three weakly supervised person re-id models have been proposed. Wang et al. introduced a differentiable graphical model [25] to capture the dependencies from all images in a bag and generate a reliable pseudo label for each person image. Yu et al. introduced the weakly supervised feature drift regularization [6] which employs the state information as weak supervision to iteratively refine pseudo labels for improving the feature invariance against distractive states. Meng et al. proposed a cross-view multiple instance multiple label learning method [5] that exploits similar instances within a bag for intra-bag alignment and mine potential matched instances between bags. However, our weak labeling setting is more practical than these three works for video person re-id. First, we do not require any strongly labeled tracklets and state information for model training. Second, we consider a scenario that the weak labels are not reliable in training data.

Our task of learning person re-id models from videos with weak supervision is also related to the problem of person search [45], [46], [47] whose objective is to simultaneously localize and recognize a person from raw images. The difference lies in the annotation requirement for training - the person search methods assume large amounts of manually annotated bounding boxes for model training. Thus, these approaches utilize strong supervision in contrast to our weak supervision.

III. METHODOLOGY

In this section, we present our proposed multiple instance attention learning framework for video person re-id. We first present an identity projection layer we use to obtain the identity-wise activations for input person images in one bag. Thereafter, two learning tasks: multi-instance learning and co-person attention mechanism are introduced and jointly optimized to learn our model. The overview of our proposed method is shown in Figure 2 and it may be noted that only the video-level labels of training data are required for model training. Before going into the details of our multiple instance attention learning framework, let us first compare the annotation cost between weakly labeled and strongly labeled video person re-id data, and then define the notations and problem statement formally.

A. Annotation Cost

We focus on person re-id in videos, where labels can be collected in two ways:

- **Perfect tracklets:** The annotators label each person in each video frame with identities and associate persons with the same identity (DukeMTMC-VideoReID [18]). Then, the tracklets are perfect and one tracklet contains one person identity. However, they are more time-consuming than ours which requires only video-level labels.

- **Imperfect tracklets:** The tracklets are obtained automatically by pedestrian detection and tracking algorithms [27], [28], [29] (MARS [32]). They are bound to have errors of different kinds, like wrong associations, missed detection, etc. Thus, human intervention is required to segregate individual tracklets into the person identities.

Our method uses only video-level annotations, reducing the labeling efforts in both the above cases. We put all person images in a video to a bag and label the bag with the video-level labels obtained from annotators. We develop our algorithm without any idea of the tracklets, but rather a bag of images. Further, we do not use any intra-tracklet loss, as one tracklet can have multiple persons in case of imperfect tracking. Table [1] and Table [11] show our method is robust against the missing annotation scenario where a person might be there in the video, but not labeled by annotators. Hence,
our framework has remarkable real-world value where intra-
camera tracking is almost surely to happen with an automated
software and will be prone to errors.

Next, we present an approximate analysis of the reduction in
annotation cost by utilizing weak supervision. Assume that
the cost to label a person in an image is $b$. Also, let the average
number of persons per image be $p$ and the average number of
frames per video be $f$. The total number of videos from all
cameras is $n$. So, the annotation cost for strong supervision is
$f p n b$. Now, let the cost for labeling a video with video-level
labels be $b'$, where $b' << b$. Thus, the annotation cost for weak
supervision amounts to $n b'$. This results in an improvement in
the annotation efficiency by $f p b/b' \times 100\%$.

B. Problem Statement

Assume that we have $C$ known identities that appear in $N$
video clips. In our weakly labeling settings, each video clip is
classification as a bag of images detected in the video,
and assigned a label vector indicating which identities appear
in the bag. Therefore, the training set can be denoted as $\mathcal{D} =
\{(X_i,y_i)\mid i = 1, ..., N\}$, where $X_i = \{I_{i1}^1, I_{i2}^2, \ldots, I_{in}^n\}$
is the $i$th bag (video clip) containing $n_i$ person images. Using some
feature extractors, we can obtain the corresponding feature
representations for these images, which we stack in the form of
the $i$th bag containing $n_i$ person images. Using some
feature extractors, we can obtain the corresponding feature
representations for these images, which we stack in the form of
a feature matrix $X_i \in \mathbb{R}^{d \times n_i}$; $y_i = \{y_{i1}, y_{i2}, \ldots, y_{ic}\} \in \{0, 1\}^C$
is the label vector of bag $i$ containing $C$ identity labels, in
which $y_{ic} = 1$ if the $c$th identity is tagged for $X_i$ (person $c$
appears in video $i$) and $y_{ic} = 0$ otherwise. For the testing probe
set, each query is a set of a collection of images with the
same person identity (a person tracklet) in a video clip.
We define two different settings for the testing gallery set as
follows:

- **Coarse-grained person re-id** tries to retrieve the videos
  that the given target person appears in. The testing gallery
  set should have the same settings as the training set -
each testing gallery sample is a bag with one or multiple
persons.

- **Fine-grained person re-id** aims at finding
  the exact
  tracklets with the same identity as the target person among all obtained tracklets. It has the same goal as the
  general video person re-id - each gallery sample is a
  tracklet with a singular person identity.

C. Multiple Instance Attention Learning for Person Re-id

1) Identity Space Projection: In our work, feature representation
$X_i$ is used to identify person identities in bag $i$. We project $X_i$ to the identity space ($\mathbb{R}^C$, $C$ is the number of person identities in training set). Thereafter, the identity-wise
activations for bag $i$ can be represented as follows:

$$\mathcal{W}_i = f(X_i; \theta)$$

where $f(\cdot; \theta)$ is a $C$ dimensional fully connected layer. $\mathcal{W}_i \in \mathbb{R}^{C \times n_i}$ is an identity-wise activation matrix. These identity-wise activations represent the possibility that each person image in a bag is predicted to a certain identity.

2) Multiple Instance Learning: In weakly labeled person re-id data, each bag contains multiple instances of person images with person identities. So the video person re-id task can be turned into a multiple instance learning problem. In MIL, the estimated label distribution for each bag is expected to eventually approximate the ground truth weak label (video label); thus, we need to represent each bag using a single confidence score per identity. In our case, for a given bag, we compute the activation score corresponding to a particular identity as the average of top $k$ activations for that identity in common. Next, we present a Co-Person Attention Mechanism for mining the potential relationships between bags.

$$p_i^j = \frac{1}{k} \text{top}k(\mathcal{W}_i[j,:])$$

where $\text{top}k$ is an operation that selects the top $k$ largest activations for a particular identity. $\mathcal{W}_i[j,:]$ denotes the activation score corresponding to identity $j$ for all person images in bag $i$. Thereafter, a softmax function is applied to compute the probability mass function (pmf) over all the identities for bag $i$ as follows, $y_i^j = \frac{\exp(p_i^j)}{\sum_{k=1}^{C} \exp(p_i^k)}$. The MIL loss is the cross-entropy
between the predicted pmf $\hat{y}_i$ and the normalized ground-truth $y_i$, which can then be represented as follows,

$$L_{MIL} = \frac{1}{Nb} \sum_{i=1}^{N_b} \sum_{j=1}^{C} -y_{ij} \log(\hat{y}_{ij})$$
for those bags with at least one person identity in common, we may want the following properties in the learned feature representations: first, a pair of bags with Person \( j \) in common should have similar feature representations in the portions of the bag where the Person \( j \) occurs in; second, for the same bag pair, feature representation of the portion where Person \( j \) occurs in one bag should be different from that of the other bag where Person \( j \) does not occur.

We introduce Co-Person Attention Mechanism to integrate the desired properties into the learned feature representations. In the weakly labeled data, we do not have frame-wise labels, so the identity-wise activation matrix obtained in Equation 1 is employed to identify the required person identity portions. Specifically, for bag \( i \), we normalize the bag identity-wise activation matrix \( \hat{W}_i \) along the frame index using softmax function as follows:

\[
\hat{W}_i[t, j] = \frac{\exp(\hat{W}_i[t, j])}{\sum_{t=1}^{T} \exp(\hat{W}_i[t, j])}
\]

(4)

Here \( t \) indicates the indexes of person images in bag \( i \) and \( j \in \{1, 2, ..., C\} \) denotes person identity. \( \hat{W}_i \) could be referred as identity attention, because it indicates the probability that each person image in a bag is predicted to a certain identity. Specifically, a high value of attention for a particular identity indicates its high occurrence-probability of that identity. Under the guidance of the identity attention, we can define the identity-wise feature representations of regions with high and low identity attention for a bag as follows:

\[
\begin{align*}
    H f_i^{j,t} &= X_i \hat{W}_i[j, :]^T, \\
    L f_i^{j,t} &= \frac{1}{n_i} X_i (1 - \hat{W}_i[j, :]^T)
\end{align*}
\]

(5)

where \( H f_i^{j,t}, L f_i^{j,t} \in \mathbb{R}^d \) represent the aggregated feature representations of bag \( i \) with high and low identity \( j \) attention region, respectively. It may be noted that in Equation 5, the low attention feature is not defined if a bag contains only one person identity and the number of person images is 1, i.e. \( n_i = 1 \). This is also conceptually valid and in such cases, we cannot compute the CPAL loss.

We use ranking hinge loss to enforce the two properties discussed above. Given a pair of bags \( m \) and \( n \) with person identity \( j \) in common, the co-person attention loss function may be represented as follows:

\[
L_{m,n}^j = \frac{1}{2} \{ \max(0, s(H f_m^{j,t}, H f_n^{j,t}) - s(L f_m^{j,t}, L f_n^{j,t}) + \delta) \\
+ \max(0, s(H f_m^{j,t}, H f_n^{j,t}) - s(L f_m^{j,t}, L f_n^{j,t}) + \delta) \}
\]

(6)

where \( \delta = 0.5 \) is the margin parameter in our experiment. \( s( \cdot , \cdot ) \) denotes the cosine similarity between two feature vectors. The two terms in the loss function are equivalent in meaning, and they represent that the features with high identity attention region in both the bags should be more similar than the high attention region feature in one bag and the low attention region feature in the other bag as shown in Figure 3.

The total CPAL loss for the entire training set may be represented as follows:

\[
L_{CPAL} = \frac{1}{C} \sum_{j=1}^{C} \frac{1}{|S|^2} \sum_{m,n \in S^j} L_{m,n}^j
\]

(7)

where \( S^j \) is a set that contains all bags with person identity \( j \) as one of its labels. \( \frac{|S^j|}{2} = \frac{|S|(|S| - 1)}{2} \).

4) Optimization: The MIL considers each bag in isolation but ignores the correlations between bags, and CPAL mines the similarity correlations between bags. Obviously, they are complementary. So, we jointly minimize these two complementary loss functions to learn our multiple instance attention learning framework for person re-id. It can be represented as follows:

\[
L = \lambda L_{MIL} + (1 - \lambda) L_{CPAL}
\]

(8)

where \( \lambda \) is a hyper-parameter that controls contribution of \( L_{MIL} \) and \( L_{CPAL} \) for model learning. In Section IV-C we discuss the contributions of each part for recognition performance.

D. Coarse and Fine-Grained Person Re-id

In the testing phase, each query is composed of a set of detected images in a bag with the same person identity (a person tracklet). Following our goals, we have two different settings for testing gallery set.

Coarse-Grained Person Re-id finds the bags (videos) that the target person appears in. So, the testing gallery set is formed in the same manner as the training set. We define the distance between probe and gallery bags using the minimum distance between average pooling feature of the probe bag and frame features in the gallery bag. Specifically, we use average pooling feature \( x_p \) to represent bag \( p \) in the testing probe set and \( x_{g,r} \) denotes the feature of \( r \)th frame in \( g \)th testing gallery bag. Then, the distance between the bag \( p \) and bag \( g \) may be represented as follows:

\[
D(p, g) = \min \{d(x_p, x_{g,1}), d(x_p, x_{g,2}), ..., d(x_p, x_{g,n_g})\}
\]

(9)

where \( d(\cdot, \cdot) \) is the Euclidean distance operator. \( n_g \) is the number of person images in bag \( g \).

Fine-Grained Person Re-id finds the tracklets with the same identity as the target person. This goal is same as the general video person re-id, so testing gallery samples are all person tracklets. We evaluate the fine-grained person re-id performance following the general person re-id setting.

IV. EXPERIMENTS

A. Datasets and Settings

1) Weakly Labeled Datasets: We conduct experiments on two weakly labeled person re-id datasets - Weakly Labeled MARS (WL-MARS) dataset and Weakly Labeled DukeMTMC-VideoReID (WL-DukeV) dataset. These two weakly labeled datasets are based on the existing video-based person re-id datasets - MARS [32] and DukeMTMC-VideoReID [18] datasets, respectively. They are formed as follows: first, 3 - 6 tracklets from the same camera are randomly selected to form a bag; thereafter, we tag it with the set of tracklet labels. It may be noted that only bag-level
labels are available and the specific label of each individual is unknown. More detailed information of these two weakly labeled datasets are shown in Table I.

We also consider a more practical scenario that the annotator may miss some labels for a video clip, namely, missing annotation. For example, one person may only appear for a short time and missed by the annotator. It will lead to a situation that weak labels are not reliable. To simulate this circumstance, for each weakly labeled bag, we randomly add 3 - 6 short tracklets with different identities into it and each tracklet contains 5 - 30 person images. So, the new bags will contain the original person images and the new added ones, but the labels are still the original bag labels. In Section IV-B, we evaluate the proposed method under this situation.

2) Implementation Details: In this work, an ImageNet [49] pre-trained ResNet50 network [50], in which we replace its last d-dimensional fully connected layer (d = 2048), is used as our feature extractor. Stochastic gradient descent with a momentum of 0.9 and a batch size of 10 is used to optimize our model. The learning rate is initialized to 0.01 and changed to 0.001 after 10 epochs. We train our model end-to-end on two Tesla K80 GPU using Pytorch. We set \( k = 5 \) in Equation 2 for both datasets. The number of person images in each training bag is set to a fixed value 100. If the number is greater than that, we randomly select 100 images from the bag and assign the labels of the bag to the selected subset. It may be noted that for WL-DukeV dataset, we split each original person tracklet into 7 parts to increase the number of weakly labeled training samples. To evaluate the performance of our method, the widely used cumulative matching characteristics (CMC) curve and mean average precision (mAP) are used for measurement.

B. Comparison with the Related Methods

1) Coarse-Grained Person Re-id: We compare the performance of our method (MIL and MIL+CPAL) to the existing state-of-the-art multiple instance learning methods - weakly supervised deep detection network (WSDDN) [30] (section 3.3 of their paper which is relevant for our case), multi-label learning-based hard selection logistic regression (HSLR) [48] and soft selection logistic regression (SSLR) [48] for the task of coarse-grained person re-id. It should be noted that we use the same network architecture for all five methods for fair comparison. From Table II it can be seen that the proposed \( k \)-max-mean-pooling based MIL method performs much better than other compared methods. Comparing to WSDDN, the rank-1 accuracy is increased by 9.8% and 11.0% for mAP score on WL-MARS dataset. When combining with CPAL (OURS) the recognition performance is further improved. Especially, compared to WSDDN, the rank-1 accuracy and mAP score are improved by 15.2% and 16.8% on WL-MARS dataset, similarly, 10.2% and 9.9% on WL-DukeV dataset.

In this subsection, we also evaluate our method under missing annotation scenario. As shown in Table II we can see that when testing our method under missing annotation situation, for WL-MARS dataset, the rank-1 accuracy and mAP score decrease 0.5% (78.6% to 78.1%) and 4.4% (47.1% to 42.7%), respectively, and for WL-DukeV dataset, it decreases 3.3% and 3.8% accordingly. Our method is not very sensitive to missing annotation situation for coarse-grained re-id task. Furthermore, we find that the proposed method with missing annotation still performs significantly better than others with perfect annotation (annotator labels all appeared identities). For example, comparing to HSLR, on WL-MARS dataset, the rank-1 accuracy and mAP score are improved by 8.5% and 7.3%, respectively.

### Table I

| Dataset | Settings | Training Set | Testing Set |
|---------|----------|--------------|-------------|
|         |          | IDs | Tracks | Bags | IDs | Tracks | Bags | IDs | Tracks | Bags |
| WL-MARS | Coarse   | 625 | -     | 2081 | 626 | -     | 1867 |
|         | Fine     | 625 | -     | 2081 | 626 | 1980  | -    | 636 | 12180 | -   |
| WL-DukeV| Coarse   | 702 | -     | 3842 | 702 | -     | 483  |
|         | Fine     | 702 | -     | 3842 | 702 | 702   | -    | 1110 | 2636 | -   |

IDs, Tracks and Bags denote the number of identities, tracklets and bags. Coarse and Fine represent coarse-grained person re-id and fine-grained setting.

### Table II

| Methods            | WL-MARS          | WL-DukeV         |
|--------------------|------------------|------------------|
|                    | R-1   | R-5   | R-10  | mAP   | R-1   | R-5   | R-10  | mAP   |
| WSDDN [30]         | 63.4  | 81.9  | 86.6  | 30.3  | 73.2  | 89.6  | 93.6  | 62.2  |
| HSLR [48]          | 69.6  | 85.9  | 89.8  | 35.4  | 77.5  | 93.0  | 95.2  | 66.0  |
| SSLR [48]          | 66.6  | 82.7  | 86.6  | 31.8  | 76.2  | 90.5  | 93.6  | 64.2  |
| MIL                | 73.2  | 89.9  | 93.3  | 41.3  | 80.8  | 93.4  | 95.6  | 69.1  |
| OURS (MIL+CPAL)    | 78.6  | 90.1  | 93.9  | 47.1  | 82.6  | 93.6  | 95.6  | 72.1  |
| OURS*              | 78.1±0.3 | 88.3±2.8 | 91.5±2.4 | 42.7±4.4 | 79.3±3.5 | 92.7±0.9 | 95.4±0.2 | 68.3±3.8 |

*OURS* represents the proposed method under missing annotation.
2) Fine-Grained Person Re-Id: In Table III we compare our framework against methods which utilize strong labels, as well as other weakly supervised methods for fine-grained person re-id. It can be seen that the proposed k-max-mean-pooling-based MIL method performs much better than most of the other compared methods and when combining with CPAL (OURS) the recognition performance is further improved. Especially, comparing to HSLR, our method can obtain 8.6% and 10.2% improvement for rank-1 accuracy and mAP score respectively, on WL-MARS, and similarly, 8.8% and 10.2% improvement on the WL-DukeV dataset. The efficacy of using weak labels is strengthened by the improvement over methods which use strong labels, such as EUG (strong labeling: one-shot setting) and UGA (strong labeling: intra-camera supervision). Weak labels also improve performance compared to unsupervised methods such as BUC, with gains of 6.4% and 8.0% in rank-5 accuracy and mAP score on WL-MARS dataset, and similarly, 6.1% and 3.0% on WL-DukeV dataset. Compared to EUG, the recognition performance is improved from 74.9% to 81.5% (6.6% difference) for rank-1 accuracy and 46.0% for mAP score. Comparing to unsupervised methods such as BUC, our method demonstrates a decrease of 5.8% and 2.3% in mAP (5.4% and 1.0% in rank-1 accuracy) on coarse and fine-grained re-id tasks by changing parameter $\lambda$. Higher $\lambda$ represents more weights on the MIL and vice versa.

We adopt a $\lambda$-max-mean-pooling activation score corresponding to a particular identity in a bag. In order to do that, we perform experiments on WL-MARS dataset, with different values of $\lambda$ (higher value indicates larger weight on MIL), and present the rank-1 accuracy and mAP score on coarse and fine-grained person re-id tasks in Figure 4.

As may be observed from the plot, when $\lambda = 0.5$, the proposed method performs best, i.e., both the loss functions have equal weights. Moreover, using only MILs, i.e., $\lambda = 1.0$, results in a decrease of 5.8% and 2.3% in mAP (5.4% and 1.4% in rank-1 accuracy) on coarse and fine-grained person re-id tasks, respectively. This shows that the CPAL introduced in this work has a major effect towards the better performance of our framework.

D. Parameter Analysis

We adopt a $k$-max-mean-pooling strategy to compute the activation score corresponding to a particular identity in a bag. In this section, we evaluate the effect of varying $k$, which is used in Equation 2. As shown in Table IV, the proposed multiple instance attention learning framework is evaluated with four different $k$ values ($k = 1, 5, 10, 20$) on WL-MARS dataset for fine-grained person re-id. It can be seen that when $k = 5$, we obtain the best recognition performance 65.0% for rank-1 accuracy and 46.0% for mAP score. Comparing to $k = 1$ which selects the largest activation for each identity, the performance is improved by 4.0% and 4.0% for rank-1


caption: Fine-grained person re-id performance comparisons. ↓ represents the decreased recognition performance compared to perfect annotation.
In an ablation study, where we use tracklet features instead of tracklets given in the bag (video). In this section, we perform Tracklet Setting on strong labels a lot. In addition, comparing the recognition performance of CV-MIML* (more than 300% relative improvement in mAP).

The one-shot labels to calculate the cost or the distribution images. However, for the sake of comparison, we implemented to our scenario where one only has access to bags of person images. Thus, CV-MIML is not directly applicable for object, activity recognition and segmentation [33], [35], [30], [36], [37]. Thus, CV-MIML is not directly applicable to our scenario where one only has access to bags of person images. However, for the sake of comparison, we implemented CV-MIML without the probe set-based MIL loss term ($L_{P}$) and cross-view bag alignment term ($L_{C,A}$), since these require the one-shot labels to calculate the cost or the distribution prototype for each class. We refer to this as CV-MIML* and compare it to our method on WL-MARS dataset for coarse-grained re-id task. We also briefly compare our results with compare it to our method on WL-MARS dataset for coarse-grained re-id task. We also briefly compare our results with

## Table IV
Fine-grained re-id performance comparisons with different parameter $k$ on WL-MARS dataset.

| $k$ | Rank-1 | Rank-5 | Rank-10 | Rank-20 | mAP |
|-----|--------|--------|---------|---------|-----|
| $k = 1$ | 61.0 | 78.5 | 83.4 | 88.0 | 42.0 |
| $k = 5$ | 65.0 | 81.5 | 86.1 | 89.7 | 46.0 |
| $k = 10$ | 60.6 | 78.0 | 83.2 | 88.4 | 41.7 |
| $k = 20$ | 57.5 | 75.9 | 81.2 | 86.0 | 38.4 |

## Table V
Coarse-grained re-id performance comparisons with CV-MIML on WL-MARS dataset.

| Methods | R1 | R5 | R10 | mAP |
|---------|----|----|-----|-----|
| CV-MIML* | 33.3 | 51.3 | 58.5 | 10.7 |
| CV-MIML [5] | 66.8 | 82.0 | 87.2 | 55.1 |
| OURS | 78.6 | 90.1 | 93.9 | 47.1 |

### E. Comparison with CV-MIML

In this section, we compare the proposed framework with CV-MIML [5] that has recently been proposed for weakly supervised person re-id task. Although [5] is presented as a weakly supervised method, it should be noted that it uses a strongly labeled tracklet for each identity (one-shot labels) in addition to the weak labels this is not a true weakly supervised setting and we term it as semi-weakly supervised. On the contrary, our method does not require the strong labels and is more in line with the weakly supervised frameworks proposed for coarse-grained re-id task. We also briefly compare our results with

| Methods | Settings | Rank-1 | Rank-5 | Rank-10 | mAP |
|---------|----------|-------|--------|---------|-----|
| HSLR [48] | Weak | 55.4 | 72.8 | 78.6 | 34.7 |
| SSLR [48] | None | 49.0 | 67.9 | 74.0 | 28.7 |
| OURS | None | 62.2 | 79.4 | 84.3 | 43.0 |
| BUC [12] | One-shot | 61.1 | 75.1 | 80.0 | 38.0 |
| EUG [18] | Intra | 62.6 | 74.9 | - | 42.4 |
| UGA [19] | - | 59.9 | - | - | 40.5 |

### F. Evaluation of Multiple Instance Attention Learning with Tracklet Setting

Our proposed method work with individual frames of the tracklets given in the bag (video). In this section, we perform an ablation study, where we use tracklet features instead of using frame-level features. So, each training sample can be denoted as $(x_t,y_t)$ where $x_t = \{T^i_1, T^i_2, \ldots, T^i_{m_t}\}$ contains $m_t$ person tracklets and $T^i_k$ is the $k$th tracklet obtained in $i$th video clip, and $y_t$ is a weak label for the bag. Tracklet features are computed by a mean-pooling strategy over the frame features. Table VI reports the fine-grained person re-id performance on WL-MARS dataset. Even in this setting, our method still performs better than others. Compared to multiple label learning-based HSLR [48], we achieve 6.8% and 8.3% improvement for rank-1 accuracy and mAP score, respectively. Compared to the state-of-the-art unsupervised BUC [12], we can also obtain better recognition performance, especially 5% improvement for mAP score. Moreover, the proposed method is also very competitive compared to those semi-supervised person re-id methods, such as EUG [18] and UGA [19], under tracklet setting. Especially, the mAP score is improved by 0.6% and 2.5%, comparing to EUG and UGA, respectively. Next, we present a more practical scenario (Noisy Tracking) where each tracklet may contain more than a singular identity due to the imperfect person tracking in a video clip.

### G. Ablation Study

In this section, we conduct ablation studies to evaluate the advantages of our proposed MIL loss and CPAL loss. We validate our methods on WL-MARS dataset under two different tasks - coarse-grained person re-id and fine-grained person re-id. From Table VII, we can see that (1) adding CPAL to other methods, such as HSLR+CPAL, SSLR+CPAL and WSDDN+CPAL helps to improve recognition performance by
Fig. 5. Illustration of coarse-grained person re-id and fine-grained person re-id results on WL-MARS dataset. (a) shows the results of coarse-grained person re-id. It demonstrates 4 retrieved bags (video clips) for a target person. Bounding boxes indicate the the most similar frame in a bag to the target person. Blue and red represent correct and wrong retrieval results. Yellow dots indicate the tracklets with the same identity as the query person. (b) shows the results of fine-grained person re-id. It illustrates 4 retrieved tracklets for a target tracklet.

Figure 5(b) shows us some results of fine-grained person re-id, in which both query and gallery samples are tracklets.

V. CONCLUSIONS

In this paper, we introduce a novel problem of learning a person re-identification model from videos using weakly labeled data. In the proposed setting, only video-level labels (person identities who appear in the video) are required, instead of annotating each frame in the video - this significantly reduces the annotation cost. To address this weakly supervised person re-id problem, we propose a multiple instance attention learning framework, in which the video person re-identification task is converted to a multiple instance learning setting, on top of that, a co-person attention mechanism is presented to explore the similarity correlations between videos with common person identities. Extensive experiments on two weakly labeled datasets - WL-MARS and WL-DukeV datasets demonstrate that the proposed framework achieves the state-of-the-art results in the coarse-grained and fine-grained person re-identification tasks. We also validate that the proposed method is promising even when the weak labels are not reliable.

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