Multi-scale Knowledge Distillation for Unsupervised Person Re-Identification

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Abstract—Unsupervised person re-identification is a challenging and promising task in the computer vision. Nowadays unsupervised person re-identification methods have achieved great improvements by training with pseudo labels. However, the appearance and label noise are less explicitly studied in the unsupervised manner. To relieve the effects of appearance noise the global features involved, we also take into account the features from two local views and produce multi-scale features. We explore the knowledge distillation to filter label noise, specifically, we first train a teacher model from noisy pseudo labels in an iterative way, and then use the teacher model to guide the learning of our student model. In our setting, the student model could converge fast in the supervision of the teacher model thus reduce the interference of noisy labels as the teacher model greatly suffered. After carefully handling the noises in the feature learning, our multi-scale knowledge distillation are proven to be very effective in the unsupervised re-identification. Extensive experiments on three popular person re-identification datasets demonstrate the superiority of our method. Especially, our approach achieves a state-of-the-art accuracy 85.7% @mAP or 94.3% @Rank-1 on the challenging Market-1501 benchmark with ResNet-50 under the fully unsupervised setting.

Index Terms—multi-scale, knowledge distillation, unsupervised person ReID.

I. INTRODUCTION

Person re-identification (ReID) aims to retrieve the same person under different camera views. It has attracted widespread attention in the computer vision community due to its great demand in practical intelligent video surveillance. Although great performance has been achieved in the supervised person ReID setting, the demand of human annotation heavily limits the further application in the real application. To make it more scalable in the real life, the task of unsupervised person ReID has been raised and attracted increasing more attention as it requires no human annotation.

Unsupervised person ReID mainly includes two categories, unsupervised domain adaptation and purely unsupervised person ReID [1]. The former aims to learn from the annotated source dataset and transfer the knowledge to the unlabeled target dataset [2]–[4], these works are proposed based on the assumption that the discrepancy between source domain and target domain is not significant. While the latter directly learns from the unlabeled target dataset, which requires no annotation information [5]–[8]. Thus, compared with the unsupervised domain adaptation setting, the fully unsupervised person ReID is more challenging and more scalable. Nowadays state-of-the-art fully unsupervised person ReID methods have achieved great improvements by training the model with the pseudo labels generated by clustering algorithm [1], [9], [10]. These methods hold the assumption that the images of the same person share higher similarity in the feature space, thus will be more likely to be collected in the same cluster. Generally, they can be regarded as two-stage training scheme, firstly a clustering algorithm is applied to divide the features of images into different clusters, and assign pseudo labels to different clusters accordingly. Then the model is trained with generated pseudo labels. These two stages are conducted in an iterative scheme until the model converges.

The key of unsupervised person ReID is to learn the discriminative and robust feature representations to distinguish from different persons accurately. Although the state-of-the-art methods achieved great progress in unsupervised person ReID, the limited representation of the single scale global feature and the noise introduced in the clustering process may hinder the learning ability of the model, thus will degenerate the performance of the model. To relieve the above problems, we propose the multi-scale knowledge distillation method for unsupervised person ReID.

Specifically, our method mainly includes two modules, the multi-scale cluster contrast learning module and the teacher guided learning module. The former maintains local and global features in their own cluster memory dictionaries and keep
them learning independently, thus encourages the model to explore more discriminative local cues. Meanwhile, the latter uses the knowledge of teacher model to guide the student model towards a more robust feature representation. As the noise will be inevitably introduced in the clustering process, the model will suffer from the label noise in the whole training process. Based on the phenomenon that the trained model is more accurate than the initialized model, intuitively the knowledge of the trained model can be utilized as the guidance to help the student model relieve the influence of noise in the training process. Our contributions can be concluded in the following:

(1) We propose a multi-scale cluster contrast learning module for unsupervised person ReID which promotes the model to discover more discriminative local cues by taking advantage of multi-scale features in the training process.

(2) We further propose the teacher guided learning module which guides the model towards a more robust feature representation by transferring the knowledge from the teacher to the student model in a multi-scale manner. To our knowledge, this is the first work to apply knowledge distillation in the offline scheme for unsupervised person ReID, and we find it is more suitable for such task.

(3) Extensive experiments are conducted on three popular person ReID benchmarks. The results show our method significantly outperforms existing state-of-the-art unsupervised person ReID methods.

II. RELATED WORKS

A. Unsupervised person ReID

Unsupervised person ReID can be summarized into two categories, unsupervised domain adaptation person ReID and purely unsupervised person ReID. The former aims to learn from the annotated source dataset and transfer the knowledge from the source domain to the unlabeled target domain [1]–[4], [11], [12]. It works based on the assumption that the discrepancy between the source domain and the target domain is not significant and applies domain adaptation techniques to tackle the problem.

While the latter category requires no annotation information and directly trains on the unlabeled target dataset [1], [9], [10]. Nowadays the state-of-the-art purely unsupervised person ReID methods tend to train the model in two stages, firstly pseudo labels are generated by dividing the dataset into diverse clusters, then the model is trained with the generated pseudo labels. These two stages are conducted in an iterative scheme until the model converges. Previous works have made great improvements on the task of unsupervised person ReID. Specifically, BUC [5] proposed a bottom-up clustering framework for unsupervised person ReID by exploiting the relation of different identities. SPCL [9] proposed a self-paced method which gradually create more reliable clusters to refine the hybrid memory and learning targets. Recently CCL [10] proposed a novel cluster contrast learning framework which built on a cluster-level cluster memory dictionary and achieved great performance. In this work, to learn a more discriminative and robust feature representation, we exploit maintaining centers of multi-scale features as independent cluster memory dictionaries in the training process, and further transfer the knowledge from the teacher model to the student model in a multi-scale manner. Thus we also discuss some works related to these techniques in the below.

B. Part-based person ReID

Most deep-based person ReID approaches take advantage of only the global feature of the person, which turns out to be sensitive to the missing key parts. To relieve the issue, recently many works focused on leveraging part discriminative feature representations. These works aim to make use of local discriminative local parts to make more accurate retrieval. Part-based person ReID can be divided into three categories. In the first category, the prior knowledge like poses or body landmarks are required to be estimated to locate the discriminative parts of the person. However, the performance of such approaches heavily rely on the accuracy of the pose or landmarks estimation models. The second category utilized the attention mechanism to adaptively locate the high activation in the feature map. But the selected regions lack of semantic interpretation [13]. The third category directly utilizes the predefined strips as it assumes the person is vertically aligned. Compared with the first category it is more scalable as it requires no pretrained modules, thus it is widely used in the person ReID and achieved great improvements in recent years. Specifically, PCB [14] conducts uniform partition on the convolution layer for learning part-level discriminative features. MGN [15] and RMGL [16] utilize multi-scale local features to get a more accurate feature representation. These methods are all proposed for supervised person ReID. Similar to our work, SSG [17] is also proposed for unsupervised person ReID and utilizes three sets of local and global features to represent persons. However, SSG generates pseudo labels by applying clustering algorithm on each set on them, which causes a huge cost of extra time computation. Furthermore, SSG updates the network with triplet loss and instance-level features, which may neglect high-level semantic meanings. Compared with SSG, our method uses the cluster center memory to capture the relation between local/global features and their own cluster centers, and our local and global branches share the same pseudo label set generated by them. We find this mechanism is effective for unsupervised person ReID.

C. Knowledge distillation

The aim of the knowledge distillation is to transfer the knowledge from the network to another. The original idea of the knowledge distillation is to compress the knowledge from the teacher network to a smaller student network. Recently, more researches have focused on self-knowledge distillation, which keeps the structure of the teacher and student network the same [18]–[21]. These methods usually directly use the outputs of the teacher whose structure is the same as the student. Specifically, a simple but effective baseline was proposed for few shot learning in [22] by minimizing the loss where the target is the distribution of class probabilities induced by the teacher model. CS-KD [19] proposed a new regularization
technique, which matches the distribution predicted between different samples of the same class. SSD [21] proposed a effective multi-stage training scheme for long-tailed recognition, which utilized the output of the teacher to generate soft label for the student. In the work, we aim to transfer the knowledge from the teacher to the student model in a multi-scale and offline scheme.

III. Method

A. Framework

As shown in Fig. 2 our framework mainly includes two components, multi-scale cluster contrast learning module and teacher guided learning module. The former aims to keep local and global feature centers as cluster memory dictionaries and keep them learning independently, which encourages the model to learn more discriminative local cues. Meanwhile, the teacher guided learning module aims to take advantage of the knowledge of the teacher model to relieve the influence of the noise introduced in the clustering process.

B. multi-scale cluster contrast learning module

To formulate our proposed method, we first introduce some notations used in the paper. Let \( X = \{x_1, x_2, \ldots, x_N\} \) denotes the unlabeled training set which contains \( N \) instances. \( F = \{f_1, f_2, \ldots, f_N\} \) denotes the corresponding feature maps extracted from the training set with the encoder \( f_0 \), which can be described as \( f_i = f_0(x_i) \). \( U = \{u_1, u_2, \ldots, u_N\} \) denotes the feature vectors got from the feature maps after the pooling operation. \( u_q \) is the corresponding feature vector of the query instance \( q \) extracted with encoder \( f_q \). \( \Phi = \{\phi_1, \phi_2, \ldots, \phi_C\} \) denotes \( C \) cluster representations in the training. Note that the number of the cluster \( C \) can vary due to clustering result before each epoch.

1) Pseudo label generation process: Although most works only utilize the global feature map for the unsupervised person ReID [2–4, 10–12], the limited representation of the single scale global features may hinder the learning of the model for differing different persons as they may be sensitive to the missing key parts. From this view, we propose the multi-scale cluster contrast learning module, which aims to take advantage of multi-scale features to encourage the model to discover more discriminative local cues to enhance the feature learning process. The procedure of the module is shown in Fig. 2. Given a unlabeled training set \( X = \{x_1, x_2, \ldots, x_N\} \), we can get the corresponding feature maps \( F = \{f_1, f_2, \ldots, f_N\} \) with the encoder \( f_0 \). Then we split feature maps in \( F \) into two parts horizontally, which are denoted as \( F^{up} = \{f_1^{up}, f_2^{up}, \ldots, f_N^{up}\} \) and \( F^{down} = \{f_1^{down}, f_2^{down}, \ldots, f_N^{down}\} \) respectively. To get the feature vectors from them, GEM pooling operations are applied on these feature branches independently. As a result, we can get three set of feature vectors respectively.

\[
\begin{align*}
U^{global} &= \{u_1^{global}, u_2^{global}, \ldots, u_N^{global}\} \\
U^{up} &= \{u_1^{up}, u_2^{up}, \ldots, u_N^{up}\} \\
U^{down} &= \{u_1^{down}, u_2^{down}, \ldots, u_N^{down}\}
\end{align*}
\]

After getting the three sets of feature vectors in equation 1 following SPCL [9] and CCL [10], we also apply DBSCAN [23] clustering algorithm on these feature vectors to generate pseudo labels. Unlike them which only utilize global features, we aim to generate pseudo labels by taking advantage of both global and local features. Specifically, with global and local feature vector sets \( U^{global}, U^{up} \) and \( U^{down} \), the pairwise distance matrix of the dataset can be obtained independently, which are denoted as \( D^{global}, D^{up} \) and \( D^{down} \). Then a re-weighted pairwise distance matrix can be obtained using the following function:

\[
D = (1 - 2\lambda_1)D^{global} + \lambda_1D^{up} + \lambda_1D^{down}
\]

where \( D \) is the re-weighted pairwise distance matrix, \( \lambda_1 \) is the balancing factor. Then the pseudo labels \( \tilde{Y} \) can be generated by DBSCAN clustering algorithm with matrix \( D \), and the cluster centroids in the memory are initialized by the corresponding mean feature vectors and the shared pseudo labels as following:

\[
\phi_k = \frac{1}{|C_k|} \sum_{i \in C_k} u_i
\]

where \( C_k \) denotes the \( k \)-th cluster. \(|\cdot|\) denotes the number of the instances in the corresponding cluster and \( u_i \) is the feature vector of the \( i \)-th sample. As shown in Fig. 2 these three branches operates Eq. 3 independently with their own feature vectors and the shared pseudo label set \( \tilde{Y} \). Thus, we can get three sets of cluster centroid representations as following:

\[
\begin{align*}
\Phi^{global} &= \{\phi_1^{global}, \phi_2^{global}, \ldots, \phi_C^{global}\} \\
\Phi^{up} &= \{\phi_1^{up}, \phi_2^{up}, \ldots, \phi_C^{up}\} \\
\Phi^{down} &= \{\phi_1^{down}, \phi_2^{down}, \ldots, \phi_C^{down}\}
\end{align*}
\]

where \( C \) is the number of the clusters, it is a variable as it may change in the training process according to clustering result before each epoch.

2) Training process: Nowadays some state-of-the-art methods maintain the feature vector of every instance in the memory dictionary and update the corresponding feature vector with its own instance in the mini-batch [9, 23]. Such methods have the problem of inconsistency in the memory updating process, as the distribution of the training data biased in the instance level [10]. To tackle the distribution inconsistency problem and update the memory in the cluster level, we use the ClusterNCE loss proposed in [10], which can be formulated as following:

\[
L^{global}_q = -\log \frac{\exp(u_q^{global} \cdot \phi^{global}_+/\tau)}{\sum_{k=0}^{C} \exp(u_q^{global} \cdot \phi^{global}_k/\tau)}
\]

where \( u_q^{global} \) is the global feature vector of the query. \( \phi^{global}_k \) is centroid global feature vector representing the \( k \)-th cluster stored in the memory. \( C \) is the number of the cluster. \( \tau \) is the temperature hyper-parameter. Naturally, the other branches can be formulated in a similar way:

\[
L^{up}_q = -\log \frac{\exp(u_q^{up} \cdot \phi^{up}_+/\tau)}{\sum_{k=0}^{C} \exp(u_q^{up} \cdot \phi^{up}_k/\tau)}
\]

\[
L^{down}_q = -\log \frac{\exp(u_q^{down} \cdot \phi^{down}_+/\tau)}{\sum_{k=0}^{C} \exp(u_q^{down} \cdot \phi^{down}_k/\tau)}
\]
(a) Pseudo label generation process: besides the global feature, centers of local features are also maintained as independent cluster memory dictionaries. In each branch, the DBSCAN clustering algorithm is applied in the re-weighted pairwise similarity matrix to generate the pseudo labels and use the shared pseudo label set and local/global features to initialize their memory cluster representations independently. (b) Training process: in each branch, query features are used to update the memory cluster representations with a momentum. The ClusterNCE loss and L2 loss are applied to update the student model. Note that the teacher model is updated in the same way but without the L2 loss. For simplicity we omit the training process of the teacher model and the warm up module of the student model.

To promote the model to discover more discriminative cues, the multi-level memory based objective function can be proposed in the following way:

$$L_{stage1} = (1 - \lambda_2) L_q^{\text{global}} + \lambda_2 (L_q^{\text{up}} + L_q^{\text{down}})$$  \hspace{1cm} (8)$$

where $\lambda_2$ is the balancing factor to balance the importance between global and local features. Then the cluster feature representations stored in the memory dictionary sets can be updated in the following way:

$$\begin{align*}
\phi_k^{\text{global}} &= m\phi_k^{\text{global}} + (1 - m)u_k^{\text{global}} \\
\phi_k^{\text{up}} &= m\phi_k^{\text{up}} + (1 - m)u_k^{\text{up}} \\
\phi_k^{\text{down}} &= m\phi_k^{\text{down}} + (1 - m)u_k^{\text{down}}
\end{align*}$$  \hspace{1cm} (9)$$

where $m$ is the momentum updating factor. $k$ is the index of the cluster query belongs to, the cluster index is the same in these three branches as they share the same pseudo label set. Note that the pseudo label generation process and training process are conducted iteratively until the model converges. In the test phase, we only adopt the global feature branch for computation efficiency.

C. Teacher guided learning module

Nowadays the training process of state-of-the-art purely unsupervised person ReID methods can be regarded as two stages. At first pseudo labels are generated by dividing the dataset into diverse clusters, then the model is trained with the pseudo labels. These two stages are conducted in an iterative
scheme [9]. [10]. However, the noise will be inevitably introduced in the convergence process as the model initialized with ImageNet pre-trained ResNet-50 performs poorly on these person ReID datasets at the beginning, which may bias the feature representation of the model. To relieve the issue, we propose the teacher guided learning module, which aims to utilize the knowledge of the teacher to guide the student model towards a more robust feature representation. For fair comparison, we take the trained model as the teacher model and the new ImageNet pre-trained model as the student model, thus the structures of these two models are the same and it requires no extra information. Our proposed teacher guided learning module works based on the assumption that although the structure of the student model has no superiority over the teacher model, the trained teacher model performs better than the initialized student model on the task of person ReID task. Thus the teacher model can provide more accurate pseudo labels at the beginning and guide the student model in the training phase through knowledge distillation.

Specifically, the teacher model is trained following Section III-B and the details can refer to Algorithm 1. The training process of the student is similar to the teacher model except that the student model is trained with the teacher guided learning module. This module includes two parts, the warm up module and the knowledge distillation module. Details about these two modules are shown in Algorithm 2. As the initialized student model performs poorly in the person ReID, the generated pseudo labels will contain numerous label noise in the early training period, thus may cause the feature representation biased. To tackle the issue, in the warm up module, we utilize the feature vectors of the trained teacher model to generate pseudo labels and initialize the cluster centroid representations in Eq. 4. Then the student is trained with the pseudo labels and fixed cluster centroid representations generated by the teacher model. In this way, the student model can learn the knowledge directly from the teacher model in a fast way to generate more accurate pseudo labels in the early period of the training phase.

In the remaining training phase, the pseudo label generation process and the training process of the student is the same as the teacher model, which is described in Section III-B except that the student model computes the objective function with knowledge distillation as following:

\[
\begin{align*}
    L_{\text{Stu}}^{\text{global}} &= L_q^{\text{global}} + \mu \frac{w_q^{\text{global}}}{\|w_q^{\text{global}}\|^2} - \frac{\hat{w}_q^{\text{global}}}{\|\hat{w}_q^{\text{global}}\|^2}^2 \\
    L_{\text{Stu}}^{\text{up}} &= L_q^{\text{up}} + \mu \frac{w_q^{\text{up}}}{\|w_q^{\text{up}}\|^2} - \frac{\hat{w}_q^{\text{up}}}{\|\hat{w}_q^{\text{up}}\|^2}^2 \\
    L_{\text{Stu}}^{\text{down}} &= L_q^{\text{down}} + \mu \frac{w_q^{\text{down}}}{\|w_q^{\text{down}}\|^2} - \frac{\hat{w}_q^{\text{down}}}{\|\hat{w}_q^{\text{down}}\|^2}^2
\end{align*}
\]  

(10)

where \(L_{\text{Stu}}^{\text{global}}\), \(L_{\text{Stu}}^{\text{up}}\), and \(L_{\text{Stu}}^{\text{down}}\) are the objective functions of three branches of the student model. \(L_q^{\text{global}}\), \(L_q^{\text{up}}\), and \(L_q^{\text{down}}\) are the ClusterNCE loss presented in Eq. 5. \(\mu\) is the bal-

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**Algorithm 1:** Training process of the teacher model

- **Require:** Unlabeled training data \(X\)
- **Require:** Initialize the encoder \(f_0\) with ImageNet-pretrained ResNet-50
- **Require:** Temperature hyper-parameter \(\tau\) for Eq.5
- **Require:** Balancing factors \(\lambda_1\) and \(\lambda_2\) for Eq.2 and Eq.8
- **Require:** Momentum updating factor \(\hat{m}\) for Eq.9

for \(n\) in \([1, \text{num\_epochs}]\)

Extract feature vector sets \(\{U_{\text{global}}, U_{\text{up}}, U_{\text{down}}\}\) from \(X\) by \(f_0\);

Clustering \(\{U_{\text{global}}, U_{\text{up}}, U_{\text{down}}\}\) into \(C\) clusters with Eq.2 and DBSCAN;

Initialize three memory dictionaries individually with Eq.3;

for \(i\) in \([1, \text{num\_iterations}]\)

Sample \(P \times K\) query images from \(X\);

Compute objective function with Eq.8;

Update cluster feature representations with Eq.9

end

**Algorithm 2:** Training process of the student model

- **Require:** Unlabeled training data \(X\)
- **Require:** Initialize the encoder \(f_0\) with ImageNet-pretrained ResNet-50
- **Require:** The teacher encoder \(f_\theta\) trained on the unlabeled training data \(X\) using Algorithm 1
- **Require:** Balancing factors \(\mu\) for Eq.10

// warm up period

Extract feature vector sets \(\{U_{\text{global}}, U_{\text{up}}, U_{\text{down}}\}\) from \(X\) by \(f_\theta\);

Clustering \(\{U_{\text{global}}, U_{\text{up}}, U_{\text{down}}\}\) into \(C\) clusters with Eq.2 and DBSCAN;

Initialize three memory dictionaries individually with Eq.3;

for \(i\) in \([1, \text{num\_iterations} \times 2]\)

Sample \(P \times K\) query images from \(X\);

Compute objective function with Eq.8;

end

// knowledge distillation period

for \(n\) in \([1, \text{num\_epochs}]\)

Extract feature vector sets \(\{U_{\text{global}}, U_{\text{up}}, U_{\text{down}}\}\) from \(X\) by \(f_\theta\);

Clustering \(\{U_{\text{global}}, U_{\text{up}}, U_{\text{down}}\}\) into \(C\) clusters with Eq.2 and DBSCAN;

Initialize three memory dictionaries individually with Eq.3;

for \(i\) in \([1, \text{num\_iterations}]\)

Sample \(P \times K\) query images from \(X\);

Compute objective function with Eq.11;

Update cluster feature representations with \(m\) and Eq.9

end
TABLE I

STATISTICS OF THREE PERSON REID DATASETS USED IN THE EXPERIMENT.

| Datasets                  | Cameras | Training | Testing |
|---------------------------|---------|----------|---------|
| Market-1501               | 25      | 751      | 3,368   |
| DukeMTMC-reID             | 26      | 702      | 2,228   |
| MSMT17                    | 27      | 1,041    | 11,659  |

For DBSCAN clustering algorithm, the maximum distance and the minimal number of neighbours are set to 0.6 and 4 as following [10].

A. Datasets and Implementations

1) Datasets: We conduct experiments on three public person Re-ID benchmarks, including Market-1501 [25], DukeMTMC-reID [26] and MSMT17 [27]. Market-1501 dataset contains 32,668 images of 1,501 IDs captured by 6 different cameras. DukeMTMC-reID dataset is another large-scale person ReID dataset, which contains 36,441 images of 702 IDs captured by 8 different cameras. While MSMT17 dataset contains 126,441 images of 1,041 IDs captured by 15 different cameras. These datasets are widely used in the person ReID tasks and the details of these three datasets are summarized in Tab. I.

2) Implementations Details: We use the Resnet-50 [38] initialized with the parameters pre-trained on the ImageNet [39] as the backbone encoder. Following existing cluster contrast framework [10], we remove all sub-module layers after layer-4 and add GEM pooling followed by batch normalization layer [40] and L2-normalization layer. During training, we use the DBSCAN [23] as clustering algorithm to generate pseudo labels at the beginning of each epoch. During test phase, we only adopt the feature vector of the first global feature branch for computation efficiency.

For training, each mini-batch contains 256 images of 16 pseudo person identities, which are resized as 256 × 128. On input images, random horizontal flipping, padding, random cropping and random erasing [41] are applied. To train our model, Adam optimizer with weight decay 5e-4 is adopted. We set the initial learning rate as 3.5e-4, and reduce it every 20 epochs for a total of 50 epochs. The balancing factor \(\lambda_1\) in Eq. [2] is set to 0.2 while the balancing factor \(\lambda_2\) in Eq. [8] is set to 0.1. The balancing factor \(\mu\) in Eq. [10] is set to 1.

For DBSCAN clustering algorithm, the maximum distance \(d\) and the minimal number of neighbours are set to 0.6 and 4 as following [10].

IV. EXPERIMENT

A. Datasets and Implementations

B. Comparison with the state-of-the-art methods

We compare our proposed method with the state-of-the-art unsupervised person ReID methods, including unsupervised domain adaptation (UDA) person ReID and fully unsupervised person ReID. The result is shown in Tab. II. We first list the state-of-the-art UDA methods, including ECN [28], MMCL [24], JVTC [29], DG-Net++ [30], MMT [31], DCML [32], MEB [33], SPCL [9] and HCD [34]. Although these methods leverage the knowledge of the source domain, our proposed method outperforms all of them on these three datasets.

Compared with the state-of-the-art fully unsupervised person ReID methods, our proposed method also achieves better performance. These methods include BUC [5], SSL [6], JVTC [29], MMCL [24], HCT [7], CycAs [35], GCL [36], SPCL [9], HCD [34], ICE [37] and CCL [10]. Specifically, as shown in Tab. II, our proposed method achieves 85.7/94.3 in mAP/rank-1 accuracy on Market-1501 and 76.2/87.4 in mAP/rank-1 on DukeMTMC-reID. On the MSMT17, our method achieves 32.4 in mAP and 61.8 in rank-1 accuracy. These results verify the superiority of our proposed method.

C. Ablation study

In this section, we study the effectiveness of different components and hyper-parameters in our proposed method. As our work is implemented based on the CCL [10], the hyper-parameters introduced in our method include: the maximum clustering distance \(d\) for the extra multi-scale branches, the balancing factors \(\lambda_1, \lambda_2\) and \(\mu\). The other hyper-parameters follow the setting of CCL.

1) Different combinations of the components in our work: As our method is combined with different modules, we conduct experiments on the three person ReID datasets described in Sec. IV-A1 versus different combinations of different components. Tab. III shows the result, as our work is implemented based on CCL, we take CCL as baseline and our modules include multi-scale branches (MS), teacher guided warm-up module (Wm) and multi-scale knowledge distillation module (KD). The result on these three datasets verifies the effectiveness of different modules in our proposed method. Specifically, from the result we can see that the combination of all these modules can achieve the best performance on Market-1501 and DukeMTMC-reID, while on MSMT17 the combination of multi-scale cluster contrast module (MG) and teacher guided warm-up module (Wm) can achieve the best result. The reason is probably that compared with Market-1501 and DukeMTMC-reID, the MSMT17 dataset is more challenging which contains more occluded images. Thus the teacher guided warm-up module (Wm) plays a more important role than the knowledge distillation module (KD) as it suffers more noise in the pseudo label generation at the beginning and the quality of the knowledge to be distilled from the teacher model is not so satisfying.

2) Balancing factors: As the aim of our proposed extra multi-scale branches is to encourage the model to explore more discriminative local cues, the weights of these branches are hyper-parameters which play an important role in our
shown in Fig. 4 the model can converge faster with knowledge distillation, which may help the model suffer from less label noise in the whole training process.

V. Conclusion

In the paper we propose the multi-scale knowledge distillation method for unsupervised person ReID. Specifically, our approach utilizes multi-scale features as independent cluster memory dictionaries to promote the model to explore more discriminative cues. Meanwhile, the teacher guided learning module is proposed to relieve the effect of the noise introduced in the clustering process. Extensive experiments on three challenging person ReID datasets demonstrate the superiority of our method.
TABLE V

| dataset       | backbone     | mAP  | R1    | R5    | R10   |
|---------------|--------------|------|-------|-------|-------|
| Market-1501   | ResNet-50    | 85.7 | 94.3  | 97.7  | 98.4  |
|               | IBN-ResNet-50| 87.3 | 94.7  | 97.7  | 98.4  |
| DukeMTMC-reID | ResNet-50    | 76.2 | 87.4  | 93.1  | 94.4  |
|               | IBN-ResNet-50| 76.8 | 87.7  | 93.1  | 94.7  |
| MSMT17        | ResNet-50    | 32.6 | 61.8  | 72.0  | 76.2  |
|               | IBN-ResNet-50| 44.2 | 71.5  | 80.8  | 84.4  |

Fig. 3. Evaluation of Hyper-parameter $\lambda_1$ and $\lambda_2$ of the teacher model on Market-1501.

Fig. 4. Accuracy of the model at each epoch during training on Market-1501.

APPENDIX A

COMPAARED WITH IBN-RESNET-50 AND RESNET-50 BACKBONES

As Instance Normalization (IN) can learn features that are invariant to appearance changes, while Batch Normalization (BN) is essential for preserving content related information, IBN-Net [42] can achieve better performance by integrating Instance Normalization and Batch Normalization. Therefore the IBN-ResNet-50 can be regarded as a stronger baseline by replacing the BN operation in ResNet-50 with IBN operation. As shown in Table V our proposed method can achieve better performance with the IBN-ResNet-50 backbone.

TABLE VI

| backbone | MSMT17 |
|----------|--------|
|          | mAP    | R1    | R5    | R10   |
| Baseline | 34.2   | 64.2  | 74.9  | 78.8  |
| Baseline+MG | 34.8 | 64.8  | 75.6  | 79.6  |
| Baseline+MS+Wm | 37.0 | 66.4  | 76.9  | 81.0  |
| Baseline+MS+KD | 37.1 | 66.5  | 76.9  | 81.0  |
| Baseline+MS+Wm+KD | 38.1 | 67.2  | 77.3  | 80.9  |

APPENDIX B

THE EFFECT OF THE CLUSTERING HYPER-PARAMETER $d$ OF THE GLOBAL FEATURE BRANCH.

As our proposed method is implemented based on CCL [10], for fair comparison the hyper-parameters of the clustering algorithm are maintained the same as CCL. In the experiment, we find that when changing the clustering hyper-parameter $d$ from 0.6 to 0.7, both of CCL and our proposed method can achieve better results on MSMT17. As shown in Table VI CCL is regarded as the baseline in the experiment. ‘MS’, ‘Wm’ and ‘KD’ represent multi-scale branches, teacher guided warm-up module and multi-scale knowledge distillation module respectively.

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