Locality Based Discriminative Measure for Multiple-shot Person Re-identification

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Abstract

Multiple-shot person re-identification tackles the problem to build the correspondence between sets of human images obtained from distributed cameras. It is challenging due to large within-class variations and small between-class differences, caused by the changing of human appearance and environment. Existing methods for addressing this issue include designing the representation to capture the within-set correlation, or crafting the measure to explore the between-set separation. This paper proposes a novel set based matching model called “Locality Based Discriminative Measure (LBDM)”, in which the discriminative potentiality of a new set-to-set distance is exploited by using the learned local metric field. As experimentally demonstrated, the proposal remarkably outperforms state-of-the-art schemes on public benchmark datasets.

1. Introduction

Person re-identification is a useful but challenging issue in visual surveillance for both academia and industry. It can be defined as the problem to judge the re-appearance for the person of interest who has been observed in deployed cameras. Identifying the detected persons in images can help either to find the criminals in real scenarios, or to tackle the false alarms and identity drifting in tracking, within a network of non-overlapping cameras. However, pose varying, illumination changing, viewpoint altering, occlusions, and possibly similar body shape and clothes style bring great challenges to solving this problem.

This paper deals with the multiple-shot re-identification case, in which for each human identity, there are multiple images available in a query as well as in the corpus. Relevant methodologies can be categorized into two paradigm-s. Some of them focus on reliable feature representing [5, 11, 13]. Although a good feature can provide a characteristic description for the appearance cue of each person, uncontrollability of the real-world complexity and subjectiveness of the hand-designing process inevitably barricade the performance enhancement. Other solutions pay attention to robust measure crafting after feature representing to deal with these problems [15, 6, 8]. However, the lack of big changes in this direction results in a quick slowing down of the performance improvement as well.

Since vector based representations of person images can be considered as points in the Hausdorff space, we can define a bundle of features extracted from multiple-shot images of the same person to be one whole set. Based on this definition, the problem of multiple-shot re-identification becomes searching a suitable distance measure for effectively matching the sets from both query side and corpus side. This geometric measure can be explored from two aspects: one is to adapt the point based distance to the set level, and the other is to study the underlying metrics for the sets. Exploration and collaboration of these two aspects might lead to a breakthrough, which motivated this work.

The main contributions of this paper are as below:

- We craft a new set-to-set distance. By measuring the global distance between majorities of samples from two sets, it is robust to irregular outliers, and also by considering the local minority of samples in each set, it can capture the information of within-set variation. (Section 3.1)

- We introduce a novel local metric learning model. It constructs a local metric field, in which the discriminative ability of the newly-proposed set-to-set distance is much enhanced. (Section 3.2)

1In this paper, we treat possibly different metrics at local areas as a field of local metrics.
We present an effective set based matching framework. It integrates the set level geometric and topological information by exploiting the set-level common-near-neighbor information based on the crafted distance; finally, set based matching is carried out by using set-level common-near-neighbor information based on the crafted distance in the learned local metric field.

2. Problem Definition and Overview of Our Approach

We reformulate the multiple-shot re-identification issue into a set based matching problem between cameras. Each set of images are generated from the detected and tracked sequences of a person in the real-world video surveillance system. Let us suppose the query sets contain images acquired from one camera, and the corpus sets are formed by images from another camera. Our target is to find the correct correspondence between query and corpus sets according to whether they belong to the same person or not. For each query set, a list will be formed by sorting the dissimilarities between itself and all the corpus sets. The matching will be evaluated by the ranking results according to the ground-truth correspondences.

The whole framework of the proposed LBDM approach is shown in Figure 1. Primarily, it is composed of three steps. Firstly, we measure the newly-proposed distance between the query and corpus sets; then, we construct the local metric field to further exploit the discriminative potentiality of this distance; finally, we match the query and corpus sets based on it.

3. Locality Based Discriminative Measure

3.1. Set-to-set Distance Crafting

To correctly match the sets, an effective set-to-set distance is important. Previous methods spotlighted minority based distance, and claimed the effectiveness of this strategy. Minority based distance takes within-set variation into account by measuring the closest local minorities of each set pair. Two exemplary methods are Minimum Point-wise Distance (MPD) and Convex Hull based Image Set Distance (CHISD). MPD measures the minimum point-wise distance between sample points from two arbitrary sets in Euclidean space. It is unstable because outliers of each class may easily disturb the distance measure and greatly change the results. CHISD tries to improve it by calculating the distance between convex hulls of two sets, instead of finding the closest pair of points from them. However, it is unavoidably influenced by the layout situation of minority of points that support the convex hulls.

Evidently, minority based distance pays much attention to the variation of sample points within the set. In contrast to it, the majority based distance, like Average Point-wise Distance (APD), describes all the point-wise distances between sets globally. This kind of distance is robust to the small number of irregular outliers in each set. Nevertheless, it is still not able to capture the information of within-set variation, so it cannot work satisfactorily.

We propose a simple but effective distance for the issue of multiple-shot person re-identification, which inherits the advantages of both minority based and majority based distances whilst overcomes their drawbacks. It is named “Mean Approach Distance (MAD)”, as it uses the mean point-to-set approach as the set-to-set distance measure. As it will be shown, such a design can get a good balance between the discrimination ability of minority based distance and the robustness of majority based distance. Let us denote \( a \) to be an arbitrary point in the set \( A \), \( b \) an arbitrary point in the set \( B \), \( l \) the point-to-point distance, and \( d \) the point-to-set distance. Thus, considering symmetry, \( D_{MAD} \) is given by:

\[
D_{MAD}(A, B) = \frac{1}{|A|} \sum_{a \in A} d(a, B) + \frac{1}{|B|} \sum_{b \in B} d(A, b).
\]

where

\[
d(a, B) = \min \{l(a, b) | b \in B\},
\]

\[
d(A, b) = \min \{l(a, b) | a \in A\}.
\]

In Equation \(1\), \( |\cdot| \) means the cardinality of a set. In E-
In the local metric learning model, to learn the local metric neighborhood determining, we make use of the set concept in its three main steps: (1) sample size. Even so, our modeling is different from existing local metric learning methods in its three main steps: (1) sample size. Even so, our modeling is different from existing local metric learning methods in its three main steps: (1) sample size.

Although the recommended minority based distance might not be the best among all the possibilities, it fits the proposed MAD measure well and has been proved to be effective, without loss of MAD’s generality.

![Figure 2](image-url) A visualization of MPD, CHISD, and MAD. Set classes can be distinguished by colors. Convex hulls are shown by polygons. Set-to-set distances are denoted by two-way arrows, and point-to-set distances in Equation 2 and 3 by one-way arrows. It is difficult to visualize MAD directly, so we draw some point-to-set distances that MAD consists of.

For easier understanding, a visualization of MPD, CHISD, and MAD has been drawn in Figure 2.

### 3.2. Local Metric Field Constructing

MAD provides a statistical way to adapt the point based distance to the set level in the feature space. To calculate a discriminative MAD, specialization of the feature space with a suitable underlying metric is indispensable. As the baseline, Euclidean metric defines the distance between two points as the length of the straight line segment connecting them. Nevertheless, this metric cannot overcome the possible weakness of a heuristic feature representation. By contrast, learned Mahalanobis metric has been proven much superior to Euclidean metric or any other ones assigned a priori \[12\] [15] [16] [14] [7].

We hypothesize all the sets stay in a local metric field, and suggest to learn possibly different local metric for each set rather than a unique global metric. Local metric has been proved very effective due to its exploitation of the distinctive locality based metrics, which can represent case-sensitive discriminative power \[10\]. To the best of our knowledge, few works have concerned local metric learning for the issue of person re-identification up to date, due to the complexity of real-world variations and limitation of the sample size. Even so, our modeling is different from existing local metric learning methods in its three main steps: (1) neighborhood determining: we make use of the set concept in the local metric learning model. To learn the local metric for each set, we determine the set-level neighborhood by utilizing the new MAD measure; (2) metric learning: we implement a ranking model instead of traditional classification models to exploit the discriminative potentiality of MAD; (3) distance measuring: we treat all the learned local metrics as points on a Riemannian manifold, and search for the suitable one for discriminative measure.

In Section 3.1 we have argued the merits of MAD. Though it is more robust to irregular outliers, unexpected set distribution may still weaken the reliability of it. A desired set based discriminative measure will conform to the criterion that intra-class distances should be smaller than inter-class distances. Here, we tighten this criterion into the sample level, because for each set in one camera, the class label (human identity) has been fixed, though unknown, for all the sample points belonging to it, and different from those in the other sets. As mentioned in Section 1, in each camera, images of the same person are treated as one set. Thus, \(l(a, b)\) in Equation 2 and 3 with a learned metric \(M\) can be expressed as \(l_M(a, b) = (a - b)^T M (a - b)\).

During local metric learning, neighborhood size needs to be determined for every query set and corpus set, respectively. We do this by selecting the pre-defined number of nearest neighbor sets by measuring MAD with an Euclidean metric at first.

We expect the learned metric to be able to improve the discriminative power of MAD. Among the existing Mahalanobis metric learning models for this issue, Optimizing Mean Reciprocal Rank (OMRR) is a good choice \[15\]. It optimizes a list-wise ranking based on Metric Learning to Rank \[9\]. Since only the rank of the first correct match is counted, the ranks of both other correct matches and any incorrect matches are arbitrary. Thus, optimizing ranking is consistent with the fact for the re-identification issue that there are large amounts of ranking instantiations of a given ground truth. OMRR is briefly described in the followings.

Given query set \(Q = \{ q \mid q \in \mathbb{R}^d \}\) and corpus set \(X = \{ x_{qi} \mid x_{qi} \in \mathbb{R}^d \}\), suppose \(\phi_{qi}(x_{qi}, q)\) is used to denote the relative feature representation of a corpus sample \(x_{qi}\) w.r.t. \(q\) and suppose \(w\) is the metric we intend to optimize. A desired ranking model could be \(g_w(x_{qi}) = w^T \phi_{qi}(x_{qi}, q)\), which scores each \(x_{qi}\). Let \(y \in X\) be a ranking of \(X\) w.r.t. the query \(q\), and \(\psi(q, y, X) \in \mathbb{R}^d\) be a vector-valued joint feature map as defined in \[15\]. Then, optimizing \(w\) for the ranking model \(g_w(x_{qi})\) is equivalent to optimizing the following model based on \(\psi(q, y, X)\).

\[
\arg \min_w \frac{1}{2} \|w\|^2 + \frac{C}{|Q|} \sum_q \xi_q \tag{4}
\]

s.t. \(w^T \psi(q, y_q, X) \geq w^T \psi(q, y, X) + \Delta(y_q, y) - \xi_q, \forall q, y \neq y_q\); \(\xi_q \geq 0, \forall q\).
where $\eta_q^*$ is the ground truth ranking of $\mathcal{X}$ for a given $q \in \mathcal{Q}$, $\xi_q$ is the slack variable, $C$ is the trade-off parameter, and $\Delta(y_q^*, y)$ is the loss function to penalize predicting $y$ instead of $y_q^*$, defined by $\Delta(y_q^*, y) = 1 - S_{mrr}(q, y)$, in which

$$S_{mrr}(q, y) = \frac{1}{|\mathcal{Q}|} \sum_{q \in \mathcal{Q}} \left\{ \begin{array}{ll} 1/r_q, & r_q < k; \\ 0, & r_q \geq k. \end{array} \right.$$  \hspace{1cm} (5)

Here, for each set, we treat samples within it to be positive and its neighborhood negative. We do so, because we find ranking on two classes instead of multiple classes makes it easier to discriminate each set from its neighbor sets of other classes. Thus, a discriminative local metric field can be constructed in each camera by learning the independent local metric for every set.

Since all the learned local metrics are $d \times d$ dimensional positive definite matrices, we can deduce they are on a differentiable manifold $\mathbb{P}_d$ with a natural Riemannian structure $\mathbf{1}$. The pair of query set and corpus set belonging to the same class will stay close in the feature space, so their local metrics will also stay near on $\mathbb{P}_d$.

Let $M_A$ and $M_B$ be the learned local metrics of two arbitrary sets $A$ and $B$ respectively. Then, there exists a unique geodesic joining $A$ and $B$. This geodesic has a parametrization as below:

$$\gamma = M_A^{1/2} (M_A^{-1/2} M_B^{1/2} M_A^{-1/2})^t M_A^{1/2}, \quad 0 < t < 1.$$  \hspace{1cm} (6)

For fairness, we use the midpoint ($t = 0.5$) of the geodesic $\gamma$ joining $M_A$ and $M_B$ on $\mathbb{P}_d$ as a new metric. This metric can be used to project the pair of query and corpus sets from the source space to the target space isomorphically. In the projected space, we can re-measure MAD between the set pair. To speed up the computation, such midpoint can also be approximated by the algebraic average of the metric pair directly.

### 3.3. Set Based Matching

With the crafted MAD and the constructed local metric field, we can perform set based matching between cameras by adopting the latest effective and efficient model, called “Set-level Common Near Neighbor Analysis (SCNNA)” $\mathbf{8}$.

Since most sets of the same class stay closer to each other than those from different classes, the sets within the same class will share more similar neighborhood structure than those from other classes. SCNNA exploits this kind of topological information to further ensure inter-class dissimilarities to be larger than intra-class dissimilarities for all sets.

SCNNA consists of a symmetric term and an asymmetric term combined by the following function:

$$D_{SCNNA}(A, B) = D_{Symmetric}(A, B) + 2\Lambda ND_{Asymmetric}(A, B).$$  \hspace{1cm} (7)

In Equation $\mathbf{7}$ $A$ and $B$ denote two arbitrary sets; $\Lambda$ is the trade-off parameter between $D_{Symmetric}(A, B)$ and $D_{Asymmetric}(A, B)$; the “Fixed-number” for the neighborhood size, denoted by $N$, is suggested to be half of the average number of sets per class. Considering symmetry, $D_{Symmetric}(A, B)$ is given by:

$$D_{Symmetric}(A, B) = D_{Fixed-number}(A, B) + D_{Fixed-number}(B, A),$$  \hspace{1cm} (8)

where

$$D_{Fixed-number}(A, B) = \sum_{i=0}^{N-1} O_B(F_A(i)).$$  \hspace{1cm} (9)

In Equation $\mathbf{8}$ $D_{Fixed-number}(A, B)$ sums the rank orders of $A$’s list’s top elements in $B$’s Rank-Order list under the setting of $N$, as shown in Figure $\mathbf{3}$ and $D_{Fixed-number}(B, A)$ is calculated in the similar way. In Equation $\mathbf{9}$ $F_A(i)$ is the $i$th element in $A$’s Rank-Order list; $O_B(F_A(i))$ returns the rank order of $F_A(i)$ in $B$’s list. Here, Rank-Order list of an assigned set is formed by the ranking of all the other sets according to their initial dissimilarities to this set.

Although effective and efficient, SCNNA has weakness. The Rank-Order lists of SCNNA are based on low-level set-to-set dissimilarity measure. Hence, the performance of SCNNA is dependent on and limited by them, whose capability is thorny and difficult to be improved nowadays.

Actually, as far as we know, the capability of low-level measure is influenced by two aspects: distance and metric. Both geometric information have been mentioned and studied in this paper. In other words, MAD and learned local metric field can complement and benefit SCNNA. Thus, their collaboration not only integrates the set level geometric and topological information, but also completes the whole framework of our proposal, namely “LBDM”.

### 4. Experiments and Results

#### 4.1. Dataset Descriptions

We set up experiments to demonstrate LBDM on several public benchmark datasets including ETHZ1,
ETHZ2, ETHZ3 \[4\], i-LIDS-MA, i-LIDS-AA \[11\], and Caviar4REID \[8\]. All of them have multiple images with spatial-temporal variations for each person, as shown in Figure 4.

![Figure 4. Exemplars from ETHZ1, ETHZ2, ETHZ3, i-LIDS-MA, i-LIDS-AA, and Caviar4REID.](image)

The ETHZ datasets \[4\] contain three video sequences of crowded street scenes, which is captured by two moving cameras mounted on a carriage. The i-LIDS-MA and i-LIDS-AA datasets are obtained from the videos of i-LIDS MCTS captured by a multi-camera CCTV network at an airport arrival hall in the busy time. From these videos, i-LIDS-MA \[11\] is made of manually annotated individual images, and i-LIDS-AA is obtained by the HOG based human detector and tracker from two cameras. The Caviar4REID dataset \[8\] is selected by hand from the less controlled recorded video of the shopping center scenarios within two different viewpoints, which include people walking alone, meeting with others, window shopping, entering and exiting shops.

4.2. Experimental Settings

We normalize all the images into 128 \(\times\) 48 pixels, and randomly select 5 (Caviar4REID) or 10 (i-LIDS-MA and i-LIDS-AA) images per person for each query set and corpus set, respectively (coming from different cameras if possible). For evaluation, we perform ten-fold cross validation with random corpus-query data splitting.

We adopt the reliable feature for our modeling, which encodes the color, texture, and edge information simultaneously by concatenating Densely-Sampled-Color-Histograms, Schmid-Filter-Bank, and Gabor-Transform \[16\]. Feature representation is not the focus of this paper, so we do not tune it for a better performance. As is well known, rising tide would lift the boat. Likewise, introducing a better feature to our model will probably result in a better performance.

The neighborhood size in the local metric learning model is set to one fifth of the number of persons in each camera. Honestly, this heuristic setting is not guaranteed to lead to the best performance of LBDM. Since different datasets may have different sample distributions, we admit that tuning this parameter may improve the performance. However, it is not discussed here due to page limitation. Since each person only has two sets (one query set and one corpus set), we follow the recommended “Fixed-number” \(N = 1\) and balancing parameter \(\lambda = 1\) for SCNNA \[8\].

4.3. Result Analysis

The state-of-the-art methods compared here include M-PCR \[5\], CHISD \[2\], APD, Mean Riemannian Covariance Grid (MRCG) \[11\], Riemannian Set-level Common-Neighbor Analysis (RSCNNA) \[8\], Custom Pictorial Structures (CPS) \[3\], Set Based Discriminative Ranking (SBDR) \[14\], and Third-Party Collaborative Representation (TPCR) \[13\]. Results are illustrated in Figure 5 and Table 1 except those on ETHZ datasets, because our approach has approached 100 percentage recognition rate on each of them, thus is superior to any other methods. In Figure 5, \(p\) denotes the person number, and \(s\) denotes the sample number for each person. Overall, it is clear that LBDM has large performance enhancement compared with the original feature it cooperates with, and thus is well ahead of all the competitors. In greater details, we can see MAD has significant advantage over the conventional minority based and majority based set-to-set distances (MPD, CHISD, and APD) on Rank-1, which is the most significant evaluating indicator for matching, and such advantage is especially remarkable on Caviar4REID. We can also check the effectiveness of local metric field constructing stage by comparing our model with it and without it, denoted by LBDM and MAD + SCNNA, respectively. Clearly, the learned local metric field contributes to a substantial performance improvement. Because extraction of the feature TPCR relies on the usage of third-party datasets, it is unfair to compare it with other methods directly. Be that as it may, LBDM is independent of the feature representation. We testify LBDM using TPCR\(^2\) and results are detailed in Table 1. Undoubtedly, our proposal still shows encouraging superiority.

5. Conclusions

This paper has proposed a novel method named “LBDM” for the problem of multiple-shot person re-identification. As a solution, an effective set based matching framework has been modeled. In it, a new set-to-set distance was crafted and its discriminative potentiality was exploited by the learned local metric field, which helped

\[\text{We follow} \quad [13] \quad \text{to extract TPCR. For the newly considered Caviar4REID, we tentatively use i-LIDS-MA + i-LIDS-AA as the third party data for dictionary construction.}\]
to enhance matching ability of high-level SCNNA. Results have testified the reliability and superiority of LBDM. Future work will include discussing the parameters which haven’t been covered in this paper due to page limitation and applying this method to across-camera tracking.

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