[1]Kalpesh Pate
[2]Jignesh Bhavsar
[3]Nirajkumar K. Chaudhari
[4]Suhas H. Patel

Enhancing Person Re-identification with Dual Cross-Camera Reciprocal Re-ranking

JES Journal of Electrical Systems

Abstract: - Person re-identification, a challenging task in computer vision, aims to align pedestrian images from different camera viewpoints to identify individuals across various locations. The primary goal of this scholarly article is to introduce a fresh and inventive methodology called Dual Cross-Camera Reciprocal Re-ranking, tailored to enhance the precision and effectiveness of re-identification systems. The innovative Dual Cross-Camera Reciprocal Re-ranking method presents a unique strategy for re-ranking in a single iteration, demonstrating a tactical approach that exploits contextual information obtained from queries. This strategy entails employing cross-camera reciprocal constraints to effectively address the intricacies inherent in the local data distribution near the queries, thereby improving the overall re-ranking process. Several extensive experiments were conducted on three widely recognized benchmark datasets, unveiling and emphasizing the exceptional and competitive performance displayed by the techniques proposed in this study when compared with the current cutting-edge methodologies in the field. This research puts forth a new re-ranking approach that utilizes reciprocal constraints across cameras to enhance the accuracy and dependability of person re-identification across diverse camera perspectives. The effectiveness of this method is demonstrated by its outstanding performance on established datasets, underscoring its potential in relation to existing methodologies.

Keywords: Person Re-identification, Feature Descriptors, Metric Learning, Re-ranking, Reciprocal nearest neighbors.

I. INTRODUCTION

The concept of person re-identification (re-ID) involves the matching of pedestrian images across different camera views. This task has gained significant interest due to its wide range of applications in areas such as video surveillance, security, biometrics, and forensics. It is a particularly challenging task because images of the same person captured by different cameras often display notable differences in lighting, pose, viewpoint, camera properties, occlusions, misalignments, and background distractions (see Fig. 1). The typically low resolution further complicates distinguishing identities based on physical attributes alone. Additionally, distinct pedestrians may wear similar attire, further complicating the task of differentiation.

Figure 1. Images from VIPeR dataset show low resolution with varying illumination, viewpoint, background, and pose. Each column displays the same person from different cameras.

Typically, metric learning methods are employed for small-scale datasets, while deep learning methods are preferred for larger datasets. Deep learning methods have demonstrated remarkable performance on extensive training datasets. However, the cost associated with obtaining extensive labeled datasets for individual camera networks in the field of person re-identification (re-ID) is a significant challenge. Additionally, deep learning methods tend to yield unsatisfactory results when applied to small-scale datasets. However, metric learning

[1,2,3,4] Assistant Professor, Electronics and Communication Engineering Department, Government Engineering College, Gandhinagar, Gujarat, India

Email: *[1]kalpesh@gecg28.ac.in, [2]jignesh@gecg28.ac.in, [3]nkc@gecg28.ac.in, [4]suhas048@gmail.com

*Corresponding author: kalpesh@gecg28.ac.in

techniques have proven to be highly effective even with limited training data. Therefore, it is imperative to focus on the advancement of efficient metric learning methods for small-scale person re-ID tasks.

The process of small-scale person re-identification (re-ID) typically involves two key stages: the development of robust feature descriptors and distance metric learning. The primary goal of the feature descriptors is to accurately capture the similarities between images of the same individual while highlighting the differences between different individuals. In the existing literature, several feature descriptors such as ELF [1], SDALF[2], WHOS[3], LOMO[4], and GOG[5] have been suggested. However, these descriptors have limitations in terms of their discriminatory accuracy due to variations in camera and scene characteristics. To address this limitation, distance metric learning [6-12] serves as the second stage in person re-ID systems. The purpose of distance metric learning is to enhance discrimination by learning a distance function that minimizes within-class variance and maximizes between-class variance. This approach effectively improves the accuracy of person re-ID systems.

To enhance the effectiveness of multiple kernel metric learning frameworks, we introduce a novel re-ranking technique that can be utilized during the testing phase of person re-ID systems. Re-ranking methods, as mentioned in previous studies [13-17], refine the ranked outcomes by learning the similarity or manifold structure of the entire test data. Our proposed re-ranking approach leverages contextual information from the complete probe (query) set and incorporates cross-camera reciprocal constraints to address the local distribution of data around each probe. By filtering out irrelevant samples from the retrieval results, we aim to improve the initial ranking list. In summary, our paper presents the following contributions: a simple yet effective dual stage re-ranking method based on the contextual information of the full probe set and cross-camera reciprocal neighborhood constraints, with the goal of enhancing the performance of multiple kernel metric learning frameworks.

II. Related Work

The enhancement of metric learning methods has led to a growing interest in re-ranking techniques in recent years. These re-ranking methods can be categorized as either semi-automatic, involving human feedback [18, 19], or fully automatic [20-22]. Several approaches have been developed to achieve robust ranking results. Barman et al. [15] approached the ranking problem as a path searching problem in graph theory. Shen et al. [23] introduced a group-shuffling random walk operation on a graph to leverage the affinity information between gallery images. DaF [24] focused on exploiting diversity from different parts of a feature vector for re-ranking. OLMANS [25] proposed a local metric adaptation approach to learn an instance-specific Mahalanobis metric for each probe. M3 [26], on the other hand, learned a series of Mahalanobis metrics for a subset of testing samples that share strong visual similarity and later employed multi-metric late fusion.

Re-ranking has demonstrated potential when incorporating nearest neighborhood information. In their study, Zhong et al. [13] introduced a re-ranking distance that combines the original distance with the Jaccard distance, which is computed using k-reciprocal features. These features are obtained by encoding the k-reciprocal nearest neighbor set into a vector using Sparse Contextual Activation (SCA). Similarly, Chen et al. [22] employed local query expansion [27] to replace each probe image, resulting in an expanded reciprocal nearest neighbor set. The distances of the corresponding neighbor set were then aggregated.

Unlike previous re-ranking methods, which often disregard the contextual information of the entire probe set, we demonstrate the potential of utilizing the neighborhood information of each test probe in relation to the full probe set. By incorporating cross-camera reciprocal constraints, we can effectively address the local distribution surrounding each probe and achieve reliable re-ranking.

III. Methodology

The act of re-ranking involves revising the order of a list based on the surrounding data of the test samples, with the goal of ensuring that the true matches in the gallery are ranked highly in the retrieved list. In this section, we present a re-ranking approach specifically designed for single-shot person re-identification. Our method is primarily inspired by two key observations:

Observation 1: In many practical scenarios of person re-identification (particularly offline scenarios), the entire test data, including all probe images, is available. However, most existing re-ranking methods only consider one probe at a time when revising the ranking list, failing to utilize the contextual information provided by the full set of probes. We have observed that leveraging the contextual information of each test probe in relation to the complete probe set can lead to improved re-ranking results.

Observation 2: While most recently proposed re-ranking methods [13, 24] perform well on large Re-ID datasets with multiple images of the same person in a gallery, their performance is less satisfactory on small Re-ID datasets with one image per person in a gallery. One possible reason for this is that these methods use a kind of query expansion [27], where the strongest matches from the gallery are added as part of the original exploration to obtain a richer latent model, and the gallery is re-queried using the expanded model. Query expansion assumes that the gallery images contain multiple viewpoints of the object of interest, so at least some true matches occupy higher ranks in the initial retrieval list, which can be added to the explored latent model later. Hence for single-shot re-ID, it would be preferable not to use query expansion.

Motivated by the observations, a novel re-ranking approach called Dual Cross-camera Reciprocal Re-ranking (DCRR) is proposed. The methodology focuses on a single-shot scenario, wherein each camera has only one image per individual. It is assumed that the entire test dataset is accessible. The approach is straightforward yet efficient, demonstrating competitive performance when compared to cutting-edge re-ranking techniques for small-scale single-shot person re-identification. Consider a set of probe images from camera A denoted as $\mathrm{P} = \{\bar{p}_1, \bar{p}_2, \ldots\ldots, \bar{p}_a\}$ and the gallery images from camera B as $\mathrm{G} = \{\bar{g}_1, \bar{g}_2, \ldots\ldots, \bar{g}_b\}$. Given a specific pivot probe image $\mathrm{p} \in \mathrm{P}$ and its retrieved rank-list $\mathrm{L_r(p, G)}$ from querying the gallery G using the distance metric $\mathrm{d(\phi(p), \phi(g))}$ based on the selected metric learning method, the aim is to establish a revised rank-list comprising k elements, ensuring a higher ranking for the correct gallery match. For $\mathrm{p} \in \mathrm{P}$, the cross-camera k-nearest neighbors is defined as,

$$\mathrm{N_k(p, G)} = \{\mathrm{g_i} \in \mathrm{G} | 1 \leq \mathrm{i} \leq \mathrm{k}, |\mathrm{N_k(p, G} = \mathrm{k}, \mathrm{d(\phi(p), \phi(g_i))} \leq \mathrm{d(\phi(p), \phi(g_r))}, \forall \mathrm{g_r} \in \mathrm{G} \backslash \mathrm{N_k(p, G)} \} \ldots\ldots. (1)$$

Pedestrian detection and feature extraction processes are inherently subject to noise, thereby implying that the acquired distance metric $\mathrm{d(\phi(p), \phi(g))}$ may not be devoid of errors. Consequently, it is plausible to encounter inaccuracies within the set of k-nearest neighbors $\mathrm{N_k(p, G)}$. To address this issue, a strategy involving the utilization of k-reciprocal nearest neighbor relationship [14] is employed, along with the implementation of additional cross-camera constraints aimed at discerning the pertinent neighbors of p from $\mathrm{N_k(p, G)}$. The cross-camera k-reciprocal nearest neighbors of p are defined as,

$$\mathrm{R_k(p, G)} = \{\mathrm{g_i} \in \mathrm{G} \mid \mathrm{g_i} \in \mathrm{N_k(p, G)}, \mathrm{p} \in \mathrm{N_k(g_i, P)}\}, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

where $\mathrm{N_k(g, P)}$ is the cross-camera k-nearest neighbors of a given gallery image $\mathrm{g} \in \mathrm{G}$.

$$\mathrm{N_k(g, P)} = \{\mathrm{p_i} \in \mathrm{P} | 1 \leq \mathrm{i} \leq \mathrm{k}, |\mathrm{N_k(g, P} = \mathrm{k}, \mathrm{d(\phi(g), \phi(p_i))} \leq \mathrm{d(\phi(g), \phi(p_r))}, \forall \mathrm{p_r} \in \mathrm{P} \backslash \mathrm{N_k(g, P)} \} \ldots\ldots. (3)$$

Our argument posits that in the case where a given element g belonging to the set of natural numbers $\mathrm{N_k(p, G)}$ is deemed a pertinent neighboring point of p, it is probable that g represents a k-reciprocal nearest neighbor of p across different cameras. To elaborate, g qualifies as a relevant neighbor of p if it resides within the k-nearest neighbors of p within the gallery set G, and simultaneously, p is encompassed within the k-nearest neighbors of g in the probe set P; essentially, both p and g stand as cross-camera k-nearest neighbors of one another. The concept of reciprocal nearest neighbor examination takes into account the local data distribution surrounding both p and g, thereby establishing a stringent and resilient interpretation of proximity in contrast to the one-directional nearest neighbor relation. It is essential to note that, unlike the approach in reference [14], the supplementary cross-camera proximity constraint where $\mathrm{N_k(g_i, P)}$used in eqn. [2] is employed to integrate the contextual insights from the entirety of the probe set P.

The cross-camera k-reciprocal nearest neighborhood relation for k = 3 is shown in Fig. 2(a). Representation of probe and gallery images for class C_j by p_j and g_j respectively. Pivot probe p_1 has k-nearest neighbors g_2, g_3 and g_1. The local distribution of classes C_2 and C_3 around p_1 is observed. Reciprocal nearest neighbors of p_1 are g_2 and g_1. However, g_3 is not included due to the absence of p_1 in its k-nearest neighbors. It is assumed that g_3 is more relevant to other probes than p_1. Cross-camera k-reciprocal nearest neighborhood constraint considers local densities and filters relevant members.

The default re-ranking list for k-reciprocal nearest neighbors is determined by sorting the filtered neighbors based on their distance from the pivot probe. Consequently, the default re-ranking list for cross-camera k-reciprocal nearest neighbors $\mathrm{R_k(p, G)}$ can be acquired as,

$$R_k^*(p,G) = \{(g_1^*, g_2^*, \ldots\ldots, g_s^*)|g_i^* \in R_k(p,G), d(\phi(p), \phi(g_i^*)) \leq d(\phi(p), \phi(g_r^*)), 1 \leq i < r \leq s\} \ldots\ldots (4)$$

The cross-camera k-reciprocal nearest neighbor constraint does not fully address the impact of local distribution of unrelated data samples around the pivot probe. In example, $R_k^*(p_1, G) = (g_2, g_1)$ where g_2 has a higher rank than g_1, despite g_1 being the correct match for p_1. This is due to class C_2 samples being distributed around p_1, placing g_2 closer to p_1 than g_1. To address this issue, a second stage of re-ranking is used to handle local data distribution. For a gallery sample g and its cross-camera k-nearest neighbors $N_k(g, P)$, the reciprocal rank list $N_k^*(g, P)$ is defined as,

$$N_k^*(g,P) = \{(p_1^*, p_2^*, \ldots\ldots, p_k^*)|p_i^* \in N_k(g,P), d(\phi(g), \phi(p_i^*)) \leq d(\phi(g), \phi(p_r^*)), 1 \leq i < r \leq k\} \ldots\ldots (5)$$

The re-ranking list $R_k^*(p_1, G)$ is obtained using eqn. [4] by analyzing the members in $R_k(p_1, G)$ from the viewpoint of p_1. By reciprocally looking at p_1 from the position of each member of $R_k(p_1, G)$ in comparison to the cross-camera full probe set P, it can be observed that the pivot p_1 occupies the first position correctly and g_2 ranks second. The rank of a pivot probe in the reciprocal rank list $N_k(g, P)$ of each member g of $R_k(p, G)$ is a valuable criterion for inferring how $R_k(p, G)$ should be re-ranked.

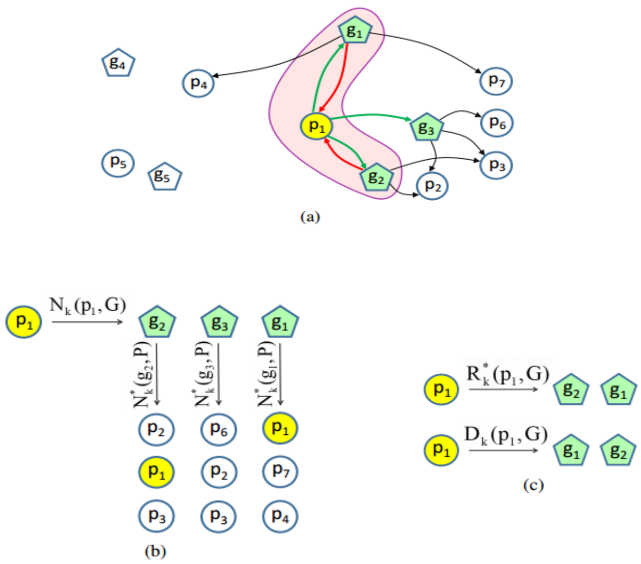

Figure 2. Illustration of Dual Cross-camera Reciprocal Re-ranking (DCRR), for k = 3

As a result, the second stage re-ranking list in DCRR is generated based on the following rule.

$$D_k(p,G) = \{(\hat{g}_1, \hat{g}_2, \ldots\ldots, \hat{g}_s)|\hat{g}_i \in R_k(p,G), \text{rank}(p, N_k^*(\hat{g}_i, P)) \leq \text{rank}(p, N_k^*(\hat{g}_r, P)), 1 \leq i < r \leq s\} \ldots (6)$$

where, the function $\text{rank}(p, N_k^*(g, P))$ denotes the position of element p within the reciprocal rank list $N_k^*(g, P)$. Consequently, for the individuals belonging to $R_k(p, G)$, the aforementioned principle involves executing a reciprocal inquiry within the comprehensive probe set P across different cameras, followed by arranging the individuals of $R_k(p, G)$ according to the ranking of the reference probe p in the reciprocal rank list $N_k^*(g, P)$ to generate the subsequent re-ranking list $D_k(p, G)$. For instance, as demonstrated in Figure 2, the outcome for $D_k(p_1, G) = (g_1, g_2)$ indicates that the correct match g_1 is appropriately positioned at the top. It is important to note that g_1 only holds the second ranking within $R_k^*(p_1, G)$.

Consequently, we exploit the contextual data of the complete probe set to reorder the components of $R_k(p, G)$ and counterbalance for the local clustering of dissimilar samples around the reference probe. It should be mentioned that the re-ordered list $D_k(p, G)$ may contain fewer than k elements due to the elimination of irrelevant neighbors from $N_k(p, G)$ during the derivation of $R_k(p, G)$. To generate an extended re-ranking list $\overline{D}_k(p, G)$ comprising k elements, instead of directly utilizing $R_k(p,G)$, we incorporate $\bar{R}_k(p,G)$ in eqn. [6]. The definition of $\bar{R}_k(p,G)$ is provided as:

$$\bar{R}_k(p,G)=R_l(p,G),\ \text{where } l = \min\ t \quad s.t.\ |R_t(p,G) \geq k| \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (7)$$

In the instance considered in Fig. 2, the process of acquiring the extended re-ranking list $\bar{D}_k(p,G)$ is delineated in Fig. 3. It should be noted that a value of $l = 4$ is necessary in eqn. [7] to guarantee that $\bar{D}_k(p,G)$ comprises $k = 3$ components.

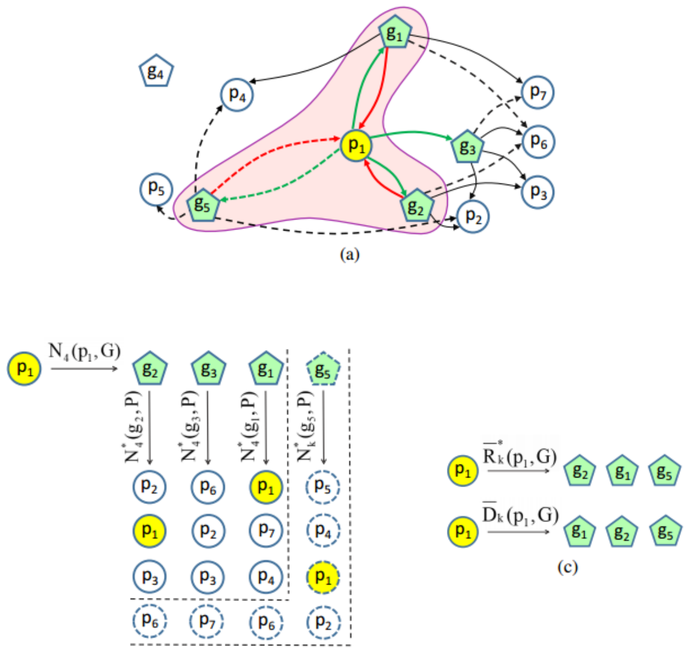

Figure 3. Ranking list expansion in DCRR (for the example illustrated in Figure. 2).

DCRR differs from existing methods by using contextual information and cross-camera constraints. It searches a reciprocal rank-list in a full probe set. It does not use Jaccard distance and query expansion. Existing methods have multiple free parameters while DCRR has only one. DCRR's performance is not dependent on its single parameter k.

IV. Results and Discussion

We executed our experiments on a variety of datasets utilizing the framework detailed in Section 3. Subsequently, we delineate the metrics of performance and the configurations of parameters employed to assess the proposed methodologies. Furthermore, a comparison is drawn with cutting-edge techniques. The assessment of our proposed approach is conducted on benchmark datasets: VIPeR, PRID450S, CUHK01, and GRID. The comparison of performance is carried out utilizing the KFDA and XQDA metric learning methodologies. During the testing phase, every probe image is matched against all gallery images. The resultant scores are organized, and the rank-K accuracy is computed based on the probability of a true match occurring within the top K rankings. This process is reiterated ten times, and the mean scores are documented. The experimental results clearly confirm the significance and superiority of DCRR for single-shot person re-ID.

Table 1 Person re-ID accuracy (in %) comparison with state-of-the-art results

Dataset	**Re-ranking Method**	**Accuracy**					
		KFDA			**XQDA**		
		Rank-1	Rank-5	Rank-10	Rank-1	Rank-5	Rank-10
VIPeR	___	47.63	77.91	88.35	48.54	77.37	87.59
	k-RNN	47.63	77.94	88.51	48.51	77.41	87.88
	DCRR	**49.94**	**79.24**	**88.86**	**51.14**	**78.16**	**88.32**

PRID-450S	__	63.69	87.47	93.38	66.93	87.82	93.56
	k-RNN	63.69	87.51	93.69	66.93	88.00	94.22
	DCRR	**67.24**	**88.76**	**93.60**	**71.20**	**90.09**	**94.49**
CUHK01	__	51.63	74.53	82.18	52.41	74.98	82.63
	k-RNN	51.65	74.59	82.43	52.47	75.06	83.09
	DCRR	**55.49**	**75.27**	**82.54**	**56.65**	**76.36**	**83.50**
GRID	__	24.40	44.46	54.96	26.64	48.64	58.80
	k-RNN	24.40	44.96	55.04	26.64	48.64	58.88
	DCRR	**24.80**	**46.72**	**57.76**	**27.36**	**49.04**	**59.36**

V. Conclusion

In this manuscript, a dual stage re-ranking strategy is introduced, aiming to refine the selection of pertinent neighbors by leveraging the contextual details of the entire probe set and reciprocal constraints across different cameras. This method adeptly manages the proximity of data surrounding the inquiries to elevate the accurate match to higher positions. Empirical evaluations conducted on standard datasets validate that the efficacy of the proposed techniques is on par with leading approaches in the field.

References

[1] Gray D, Tao H. Viewpoint invariant pedestrian recognition with an ensemble of localized features. In: Proceedings of the European Conference on Computer Vision (ECCV); 2008, Available from: https://dl.acm.org/doi/10.1007/978-3-540-88682-2_21.

[2] Bazzani L, Cristani M, Murino V. Symmetry-driven accumulation of local features for human characterization and re-identification. Computer Vision and Image Understanding. Available from: https://doi.org/10.1016/j.cviu.2012.10.008.

[3] Lisanti G, Masi I, Bagdanov AD, Del Bimbo A. Person re-identification by iterative re-weighted sparse ranking. IEEE Transactions on Pattern Analysis and Machine Intelligence. Available from: 10.1109/TPAMI.2014.2369055.

[4] Liao S, Hu Y, Zhu X, Li SZ. Person re-identification by local maximal occurrence representation and metric learning. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2015.

[5] Matsukawa T, Okabe T, Suzuki E, Sato Y. Hierarchical Gaussian descriptor for person re-identification. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2016.

[6] Xiong F, Gou M, Camps O, Sznaier M. Person re-identification using kernel-based metric learning methods. In: Proceedings of the European Conference on Computer Vision (ECCV); 2014.

[7] Koestinger M, Hirzer M, Wohlhart P, Roth PM, Bischof H. Large scale metric learning from equivalence constraints. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2012.

[8] Liao S, Li SZ. Efficient PSD constrained asymmetric metric learning for person re-identification. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV); 2015.

[9] Zhang L, Xiang T, Gong S. Learning a discriminative null space for person re-identification. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2016.

[10] Ali TMF, Chaudhuri S. Maximum margin metric learning over discriminative nullspace for person re-identification. In: Proceedings of the European Conference on Computer Vision (ECCV); 2018.

[11] Prates R, Schwartz WR. Kernel cross-view collaborative representation-based classification for person re-identification. Journal of Visual Communication and Image Representation. 2019; 58:304-315.

[12] Qi L, Liu Z, Shi Y, Geng X. Generalizable Metric Network for Cross-domain Person Re-identification. IEEE Transactions on Circuits and Systems for Video Technology. 2024. doi: 10.1109/TCSVT.2024.3395411.

[13] Zhong Z, Zheng L, Cao D, Li S. Re-ranking person re-identification with k-reciprocal encoding. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2017.

[14] Bai S, Bai X, Tian Q. Scalable person re-identification on supervised smoothed manifold. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2017.

[15] Barman A, Shah SK. Shape: A novel graph theoretic algorithm for making consensus-based decisions in person re-identification systems. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV); 2017.

[16] Zhao R, Liu J, Zhao Z, He Z, Su F. Situational diversity in video person re-identification: introducing MSA-BUPT dataset. Complex & Intelligent Systems. 2024 May 23; 1-7.

[17] Chen Y, Li Z, Song A. Multi-Query Person Search with Transformers. In: Pacific-Asia Conference on Knowledge Discovery and Data Mining; 2024 May 1; Singapore. Singapore: Springer Nature Singapore. p. 116-128.

[18] Liu C, Loy CC, Gong S, Wang G. Pop: Person re-identification post-rank optimisation. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV); 2013.

[19] Wang H, Gong S, Zhu X, Xiang T. Human-in-the-loop person re-identification. In: Proceedings of the European Conference on Computer Vision (ECCV); 2016.

[20] Yuan M, Yin D, Ding J, Zhou Z, Zhu C, Zhang R, Wang A. A multi-image joint re-ranking framework with updateable image pool for person re-identification. Journal of Visual Communication and Image Representation. 2019; 59:527-536.

[21] Wang S, Zhang X, Chen L, Zhou H, Dong J. Asymmetric filtering-based dense convolutional neural network for person re-identification combined with joint Bayesian and re-ranking. Journal of Visual Communication and Image Representation. 2018; 57:262-271.

[22] Chen Y, Yuan J, Li Z, Wu Y, Nouioua M, Xie G. Person re-identification based on re-ranking with expanded k-reciprocal nearest neighbors. Journal of Visual Communication and Image Representation. 2019; 58:486-494.
[23] Shen Y, Li H, Xiao T, Yi S, Chen D, Wang X. Deep group-shuffling random walk for person re-identification. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2018.
[24] Yu R, Zhou Z, Bai S, Bai X. Divide and fuse: A re-ranking approach for person re-identification. In: Proceedings of the British Machine Vision Conference (BMVC); 2017.
[25] Zhou J, Yu P, Tang W, Wu Y. Efficient online local metric adaptation via negative samples for person re-identification. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV); 2017.
[26] Zhou J, Su B, Wu Y. Online joint multi-metric adaptation from frequent sharing-subset mining for person re-identification. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2020.
[27] Chum O, Philbin J, Sivic J, Isard M, Zisserman A. Total recall: Automatic query expansion with a generative feature model for object retrieval. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV); 2007.