Robust and Efficient Person Re-Identification Model using K-Nearest Neighbor Graph

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Abstract—the state-of-art person re-identification (prid) models for ranking generally depends on labeled pairwise feature sets information to learn a task-dependent distance metric. Further, in retrieval process, re-ranking is an important mechanism for enhancing the accuracy. However, very limited work is carried out for designing a re-ranking method, particularly for automatic and unsupervised strategies. The existing re-ranking based prid model is not efficient when multiple persons appears simultaneously in second camera. This is because the existing model identify person in second camera by matching the feature sets with feature sets in first camera, individually with respect to other person in the second camera. For overcoming research problem, this paper present robust and efficient prid (reprid) model. First, present a robust learning/ranking method using k-nearest neighbor (knn) graph. Then, this work present a re-ranking method to improve accuracy of prid by using information of co-occurrence persons for matching and reorganizing given rank lists. Experiment are conducted on standard dataset shows robustness and effectiveness of proposed prid method.

Keywords— surveillance applications, person identification, knn, re-ranking.

I. INTRODUCTION

Advancement in several technologies such as storage devices, large scale video data, compression technique and the networks have become easily accessible to the normal users and meanwhile it has become the tough task to browse the relatable data in accordance with the huge video datasets. Normally information about the person is one of the eminent clues when people recall their video contents. Moreover, the identification of particular person is very important based on the video summary, the primary intention behind the Time
Identification is for associating the each and every subjects which occur in the video clips with the real person. Moreover, the manual labeling of all these subjects in large-scale video is very difficult as it is costly. Consuming and labor intensive. Hence to deal with such things face recognition[2] and face detection [1] were introduced but the traditional approach of FR are not even nearer to support the practical and reliable identification.

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Even in case of less number of people appeared in the video due to the lack of information as the appearance of single person is provided for identifying the objects.
Identification of person becomes critical considering the variation in face expression, pose, illumination, this makes difficult to identify [3].
Moreover Re-Identification of the person [4], [5], [6], [7] has become one of the most considerable approach in the past few decades, however the previous proposed approach focused on the two main aspects i.e. metric learning and feature extraction as featu
re extraction helps in learning the discriminative representations and robust of the particular person [8] [9]. Metric learning helps in learning a new distance or the similarity metric that helps in differentiating between the two persons [10] [11]. Several factors that acts as the obstacle for achieving the low accuracy such as light , pose variation and occlusion are to name a few, hence the re-ranking plays eminent role and it can improvise the process of re-id, the main purpose of the re-ranking algorithm is to return the more positive instances in the list of top rankings. Despite of all these scenario limited research has been done for re-ranking technique mainly for those that are FAU (Fully automatic unsupervised) solutions.
Hence in past various technique has been proposed some of them are as [12] was proposed for exploiting the similarity relationship among the top-ranked images in the first ranking list. However the main drawback of the KNN method is that wrong match may get the highest priority in the initial ranking list and this may lead to the inclusion of noise and affect the result. Hence [13] proposed the k-reciprocal nearest neighbors (KRNN) to overcome the problems of KNN based method presented above. Using KRNN based PRID method, two images are considered top-k ranked where one of them are top ranked and the other is considered as the probe and they were named as k-reciprocal neighbors (KRN) [14], [15]. For building effective re-ranking method it is important to build efficient preliminary ranking list. The model presented in [14] showed that higher ranks are given to some false matches. For reducing interference of mismatches [14], [15], KRNN is introduced. However, the existing model are not efficient under extreme variation in pose, illumination and expressions. Along with, they induce computation overhead for PRID. Thus, it is important to extract smooth intrinsic geometry for ranking task of different individual sharing common visual characteristics. Further, in existing PRID model, the probe images of a person are considered individually. Then, they generate distance from benchmark data to a probe image and construct a rank list.

Nonetheless, in actual environment there exist multiple person appearing simultaneously within a particular camera. Thus, we can use these information to improve accuracy of prediction. For overcoming research problems and challenges, this work presented a robust PRID method that is autonomous and unsupervised nature. First, present an efficient ranking method. Then, this work present a novel re-ranking method using Information of co-occurrence persons for matching and reorganizing given rank lists. Our model assign penalties (i.e., update score) to every highly ranked benchmark image in other list. The penalties are estimated using similarity feature set benchmark image to probe image.

The Contribution of research work is as follows:

- This work presented a robust learning and re-ranking method for PRID that is autonomous and unsupervised in nature.
- The proposed re-ranking model can be used to enhance the accuracy of any supervised PRID model.
- The proposed PRID model attains higher matching rate performance when compared with varioys state-of-art PRID model.

The rest of the paper is organized as follows. In section II the literature survey various existing person identification and re-identification using machine and deep learning is discussed. In section III, the proposed robust learning and re-ranking method for person re-identification method is presented. In penultimate section experimental study is carried out. The conclusion and future direction of research work is discussed in last section.

II. LITERATURE SURVEY

Person identification using CCTV aid surveillance application in identifying theft, tracking malicious user, detecting terrorist interception and so on. Further, it can also be utilized in identifying people with suicidal intention or person with any problem by performing classification using facial expression. Thus, this section conducts survey of recent PRID method. **Feature extraction** [8], [9] [16], [17] is one of the important step in the Re-identification of particular person, moreover [16] proposed a technique with deep learning where the FE is transferred gradually from the traditional approach to the deep learning approach, similarly. [34] Proposed the color histogram along with HOG, which are applicable for the visual features of the particular person. [16] Has given the detailed review report of the person re-identification. Moreover, the main drawback of [16] was that High dimensional features of computer vision fail to capture the invariant factors under the sample variances. Moreover, an ideal distance metric also plays as an important tool for the Hand Crafted feature but the metric learning might not work in case of the deep feature and the main reason behind this is it has learned sufficient information for the robust feature of that particular person and for the detailed [11] and [16] can be referred.

In past several person identification technique has been proposed these have mainly focused on the metric learning [19] or the feature learning [18], other technique as discussed in [20-24] have focused on the re-ranking technique, for the re- identification and it totally differs from paper [25] and [26]. These two requires either label supervision or human interaction and it focus on the unsupervised and automatic solution. Moreover [27] has developed re-ranking technique through analyzing the direct information and relative information of the nearest neighbor of the each images. In [20] proposed a re-ranking model based on the unsupervised learning and it is developed by integrating the context and content information in the given list, this in terms effectively discards the ambiguous sample for improving the Re-Identification performance. In [23] presented the ranking method based on the bidirectional for revising the initial ranking with new measured similarity, this similarity is measured as the fusion of both. In Recent for re-ranking, task common nearest neighbors of various baseline methods [24] and [28]. In [28] the two methods were integrated i.e. local features and global features of common nearest neighbors as the novel queries later it is revised through aggregating the ranking list of local features and global features. In [24] KNN is used for computing both difference and similarity from the various baseline method. Moreover, the aggregation is performed for optimizing the ranking list. Moreover, the continuous progress of the above mentioned research work in re-ranking does provide the promising future for discovering the information from KNN. However the limitation of the KNN is that it might restrict the overall performance as false match are also include to overcome this [14], [15] presented KRNN based PRID. However, these models induce computation overhead and are not efficient against illumination and pose variation. Along with, these models are not efficient when multiple probe exist simultaneously. Thus, from overall survey it is seen there is need to develop an efficient learning and re-ranking model that overcome above problem. In next section this work presents a robust and efficient learning and re-ranking model for PRID.

III. A ROBUST LEARNING AND RE-RANKING MODEL FOR PERSON RE-IDENTIFICATION

This section presents robust learning and re-ranking model for person re-identification. First, the work describe the mathematical representation of research problems. Here the work considers that there is only one image is present for each person within a **probe/test set benchmark** for person identification. Further, consider architecture of re-ranking for PRID with l target persons appearing concurrently as shown in Fig. 1.

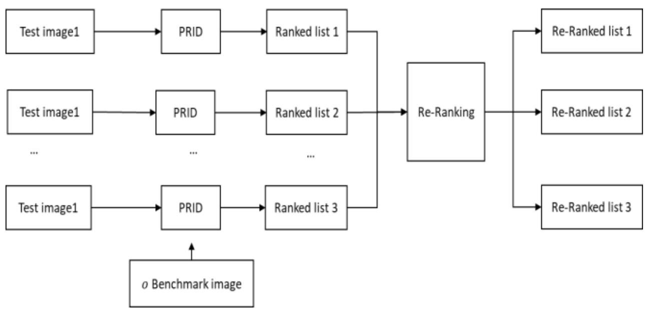

Fig. 1. Architecture of re-ranking for PRID with l target persons appearing concurrently.

For every probe/test image, first the model extracts d −dimension feature vectors, depicted as follows

$$y = (y_1, \dots, y_e)^U \in \mathcal{S}^e. \quad (1)$$

Let consider a test scenario y^q, the model initialize it with certain a positive ($+ve$) ID/label$+1$, and extents this probing data to o unlabeled benchmark scenarios $\{y_j^h\}_{j=1}^{o}$, every instance will have preliminary ID 0. The vector sets of preliminary ID initialization is mathematically expressed as follows

$$z = (z_1, \dots, z_{o+1})^U, \quad (2)$$

with $z_j = 1$, if $y_j = y^q$, $z_j = 0$ otherwise.

We define a combined set $W \rightarrow y^q \cup \{y_j^h\}_{j=1}^{o}$, and denote a learning function as $f: W \rightarrow \mathcal{S}$. With the function the PRID model target for computing a learning score (LS) vector sets

$$d = (d_1, \dots, d_o)^U, \quad (3)$$

so that each instance y_j^h has a score d_j.

a) K-nearest neighbor graph construction:

In proposed learning method the first the unknown manifold is approximated using K-nearest neighbor graph $H = (W, F)$ well-defined on W. The edge sets F are weighted using pairwise affinity matrix (AM) $B \in \mathcal{S}^{(o+1)*(o+1)}$ described using following equation

$$B_{jk} = exp\left(-\mathbb{D}^2\left(y_j, y_k\right)/\mu^2\right), \quad (4)$$

where μ depicts the scaling parameter, for $j \neq k$ and $B_{jj} = 0$. An important thing to be noted here is that the diagonal elements (DE) of B are established/fixed to 0. This is done for avoiding self-reinforcement in process of label propagation. The distance metric (DM), $\mathbb{D}: W * W \rightarrow \mathcal{S}$ in unsupervised PRID leaning environment is generally described utilizing Euclidean distance (ED). Nonetheless, if the associations among image sets are well-known and Id is initialized, the model can learn a task-centric DM [29]. Utilizing the supervised learning metrics efficiently 'distort' the implied embedding space estimated in proposed learning method. The work experimentally shows using proposed learning method with supervised learning metrics aid in enhancing PRID outcome than just only employing supervised learning metrics.

Construction of graph G from beginning every instance a new test condition is seen can induce significant computation overhead. Especially, when estimating AM, which significantly induce a complexity of $O(n^2)$. Thus, it is computationally infeasible. For avoiding computational overhead, we can pre-estimate the AM of benchmark test case scenarios offline $B^h \in \mathcal{S}^{o*o}$. Thus, when a new test case is detected, the model can estimate

$$e_{q-h} = \mathbb{D}\left(y^p, y_k^h\right) \quad (5)$$

and increment the dimensionality size of AM within B^h to

$$B = \begin{bmatrix} O & e_{q-h} \\ e_{q-h}^U & B^h \end{bmatrix}. \quad (6)$$

Thus, the computation complexity (CC) is now linear in nature with respect to size of benchmark to be tested.

b) Proposed learning method:

Using Eq. (6) the model can compute the un-normalized graph Laplacian (UNGL) M_v and normalized graph Laplacian (NGL) M_o for a given B using following equation

$$M_o = J - E^{-\frac{1}{2}} B E^{-\frac{1}{2}} = J - T, \quad (7)$$

$$M_v = E - B, \quad (8)$$

where E depicts a DM considering $D_{jj} = \sum_k B_{jk}$. Subsequently the closed-form strategies of both learning method described using following equations

$$Learning - M_o : d = (\varphi J + M_o)^{-1} z, \quad (9)$$

$$Learning - M_v : d = [(\varphi J + M_v)^{-1}]^n z, \quad (10)$$

where $\varphi \geq 0$ depicts a parameter that is mutual for both of the learning method described in Eq. (9) and Eq. (10), while $n \geq 0$ is precise for $Learning - M_v$.

First, the work describes overview of $Learning - M_o$. Let $\beta = 1/(1 + \varphi) \in [0,1]$. The basic thought/concept is to compute the below equation in iterative manner

$$g(u + 1) = \beta T g(u) + (1 - \beta) z. \quad (11)$$

For every iteration u, every case study obtains propagated Ids from its respective neighbors (first term), and keeps its preliminary ID initialized (second term). The remaining of first and second term is optimized using β (**thus the φ**). For obtaining the bound of sequence $\{g(u)\}$ as the learning score vector d the process is repeated till it reaches convergence [30].

A closed-form strategy is acquired by establishing the bound of $g(u)$ when it is converged with respect with d. Thus, by substituting $g(u + 1)$ and $g(u)$ in Eq. (11) with d, will obtain

$$d = \beta T d + (1 - \beta) z \quad (12)$$

$$(J - \beta T) d = (1 - \beta) z \quad (13)$$

$$d = (1 - \beta)(J - \beta T)^{-1} z \quad (14)$$

where J depicts identity matrix (IM). Further, the model can neglect global influence (GI) $(1 - \beta)$ for learning without modifying the outcomes. Then, by changing $\beta = 1/(1 - \beta)$ and $M_o = J - T$ in Eq. (14), the model can have closed-form strategy in **Eq. (4)**, $d = \frac{1}{1+\varphi}(J + \varphi J - T)^{-1} z \equiv (\varphi J + M_o)^{-1} z$.

The $Learning - M_o$ is subtle to the parameter of $\boldsymbol{\varphi}$ because of usage of M_o. For being more precise as shown in [31], the learning function (LF) shows the resulting mathematical representation if $\varphi$is trivial in nature

$$d = \frac{w_1(y)}{\varphi + \alpha}, \quad (15)$$

where α is a minor discriminative parameter important for learning. $w_1(y)$ depicts primary eigenvector (EV) sets of M_o, which can be estimated by the non-constant density $q(y)$. Considering a job of PRID, $q(y)$ is not uniform in nature considering the dynamic nature of respective person presences distributed in imbalanced nature? Thus, because of that, the $w_1(y)$ is a function dissimilar to the relevance organization of probing conditions, and the outcome d will also be uninformative. Along with, the small φ value results in bad outcome in $Learning - M_o$.

The $Learning - M_v$ is more robust to φ when compared with $Learning - M_o$. This is because M_v is composed of a constant

$$w_1(y) = \left(\frac{1}{\sqrt{1+o}}, \dots, \frac{1}{\sqrt{1+o}}\right)^U, \quad (16)$$

Thus the $w_1(y)/\varphi$ doesn't impact the concluding learning score.

In $Learning - M_v$, the $(\varphi J + M_v)^{-1}$is increase with respect to power of n for overcoming the diverging issues [31], that is, where entire probing condition have 0 rank in the bound of infinite unlabeled probing conditions. The overall flow of proposed robust and efficient person re-identification model is described in **Algorithm 1**.

Algorithm 1: Learning model for person identification.
Input: a person image feature set y^q, benchmark $\{y_j^h\}_{j=1}^{o}$;
Output: re-computed learning score d''
Step 1. Start
Step 2. Initialize training and feature extraction process;
Step 3. Pre-establish affinity matrix $B^h \in \mathcal{S}^{o*o}$ for benchmark;
Step 4. Define preliminary label assignment as $z = (z_1, \dots, z_{o+1})^U$, with $x_j = 1$ if $y_j = y^q$, and $z_j = 0$ otherwise;
Step 5. Initialize learning and testing process
Step 6. Obtain testing person image feature sets y^q;
Step 7. Estimate $\mathcal{D}\!:\left(y^q, y_k^h\right)$;
Step 8. Increase affinity matrix from B^h to B using Eq. (4).
Step 9. Evaluate the graph Laplacian M_o using Eq. (7) or M_v using Eq. (8).
Step 10. Evaluate learning score d using Eq. (9) or Eq. (10).
Step 12. Re-compute score
Step 13. For $j = 1 \rightarrow Length\left(M_j\right)$ **do**
Step 14. For $k = 1 \rightarrow j$ **do**
Step 15. Compute $P\left(Image_j, M_k\right)$ using Eq. (17) or Eq. (18).
Step 16. End For
Step 17. End For
Step 18. For $j = 1 \rightarrow Length\left(M_j\right)$ **do**
Step 19. For $k = 1 \rightarrow j$ do
Step 20. Compute $d''\left(Image_j, M_k\right)$ using Eq. (19)
Step 21. End For
Step 22. $M_j = sort\left(d''(j)\right)$;
Step 23. End For
Step 14. Stop.

Considering that we possess l test case individual arriving at same instance and o benchmark individuals, utilizing PRID model, l learned rank sets and learning scores of the benchmark data's in every ranked list (lower score depicts lower distance with respect to testing image, and thus, more identical to test image and vice versa) are collected. Higher the similarity with probing image a benchmark image is, the high probability ranking it will be in other list sets of probing image sets. Thus, this work includes a penalty score estimated for every benchmark of each rank list. The learning score of benchmark image sets in every list is optimized utilizing penalty parameter and the ranked list set is reordered based on new optimized ranking score.

The penalty score of every benchmark images considering every rank list are estimated using distance of that image with respect to probing image of the rank list by utilizing penalty function (PF). Thus, lesser penalty will be given to respective rank list considering higher variation to the probing image a benchmark is. This work present 2 PF, namely P_A and P_B. Nonetheless, varied functions with characteristic described above can be used, irrespective of the framework for PRID.

$$P_A = P\left(Image_j, M_k\right) = e^{-dist^2\left(Image_j, Probe_k\right)/\delta^2} \qquad (17)$$

$$P_B = P\left(Image_j, M_k\right) = \frac{1}{1 + e^{-dist^2\left(Image_j, Probe_k\right)/\rho^2}} \qquad (18)$$

where $Image_j$ is the j^{th} benchmark image. Probing image k depicts the k^{th} probing image, and M_k is its respective ranking list. The distance function (DF) depicts the trustable/confidence scores of being the identical individual among 2 images. That score are preliminarily obtained by PRID model. The parameter δ and ρ are used for controlling the differences of PF outcomes. Benchmark image sets in the preliminary list are ranked by using its trustable score with probing image. This work considers the score obtained in one list are optimized utilizing PF estimated outcome from other lists.

$$d''\left(Image_j, M_k\right) = d\left(Image_j, M_k\right) + \frac{1}{l-1}\sum_{r \neq k} P\left(Image_j, M_r\right). \qquad (19)$$

where $d\left(Image_j, M_k\right)$ and $d''\left(Image_j, M_k\right)$ are, respectively, the original distance and optimized distance among benchmark image sets and the probing image of the list, $Image_j$ depicts j^{th} benchmark image, M_k depicts the k^{th} list, and l is the number of individual present in same instance in a video/image. Higher penalties of a benchmark image in a list will increase the distance of that image to the probing image sets in other lists. The final rank list are obtained by categorization image sets according to its new improved score. The proposed learning and re-ranking based PRID will aid in attaining better matching accuracy when compared with experiment model which is experimentally shown below.

IV. RESULT AND ANALYSIS

This section presents experiment analysis of proposed person identification method performance over exiting person identification method.

a) Experiment setup and performance metric evaluation:

The system environment used for experiment analysis is Windows 10 enterprises edition, Intel Pentium I-7 class Quad core processor, 16 gigabits memory, and NVIDIA graphical processing unit that has CUDA compatibility. The proposed person identification model is implemented using MATLAB and Python 3 libraries. The performance is evaluated in terms of Cumulative matching characteristics (CMC) and mean average precision (mAP). Experiment is conducted on standard dataset such as VIPER and ILIDS. This work considers re-ID as ranking issues. Thus, we describe cumulative matching accuracy at rank-1. Further, mAP is considered as object retrieval issues [19].

b) Feature extraction for person re-identification using proposed ranking model:

Person re-identification with proposed ranking model is applied to [32]. This work used [32] because person re-identification model is designed considering sparse label smoothing regularization (SLSR). Further, to depict person appearance, Local Maximal Occurrence (LOMO) features are used [33]. Thus, the model is robust to illumination variations and view changes.

c) Dataset:

The dataset used for experiment analysis is discussed in this section. **VIPeR Dataset:** The dataset is composed of 1264 images of 632 different persons [34] and is used widely for various person re-identification methods.

The dataset is normalized to 128*64pixels similar to [35]. Each person has two images from two different camera views. The major challenges involved using VIPeR dataset are the huge variance in viewpoints, poses, illumination, low-resolution and lighting conditions. For analysis, the data is randomly split into training and testing sets. Further, the galley image pair and probe image are also chosen in random manner. **i-LIDS Dataset:** The dataset is composed of video images content of a very busy airport arrival arena. The dataset is composed of 479 images of 119 personals. The dataset is normalized to 128*64pixels similar to [35]. On an average each individual has 4 images. The image captured through non-overlapping cameras. Further, the capture images are subject to large illumination variations and occlusions. Similar to VIPeR dataset, the data is randomly split into training and testing sets. Further, the galley image pair and probe image are also chosen in random manner.

d) Experiment outcome on VIPeR Dataset:

This section present experiment outcome attained by proposed person re-identification model over state-of-art existing person re-identification model for VIPeR dataset. The outcome of Rank-1, Rank-5, rank-10, rank-15, and rank-20 is shown in Table 1 and is graphically shown in Fig. 2 and Fig.3. From result attained it can be seen the proposed person re-identification model improves matching rate performance by 22.206%, 11.68%, 6.66%, 2.1%, and 3.575% over existing person re-identification model [35] considering Rank-1, Rank-5, rank-10, rank-15, and rank-20, respectively. Similarly, the proposed person re-identification model improves matching rate performance by 5.472%, 6.655%, 3 3.44%, and 2.707% over existing person re-identification model [32] considering Rank-1, Rank-5, rank-10, and rank-20, respectively.

Table 1: Matching rate performance evaluation for person re-identification by proposed model over state-of-art

Authors/Rank	**1**	**5**	**10**	**15**	**20**
De cheng et al., [35]	54.3	77.1	85.5	93.1	94.4
JP. Ainam et al., [32]	65.98	81.49	88.45	-	95.25
Our approach	**69.8**	**87.3**	**91.6**	**95.1**	**97.9**

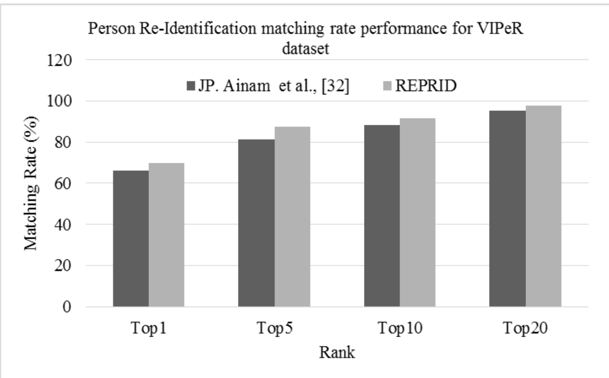

Fig. 2. Matching rate performance evaluation for person re-identification.

e) Experiment outcome on i-LIDS Dataset:

This section present experiment outcome attained by proposed person re-identification model over state-of-art existing person re-identification model for i-LIDS dataset. The outcome of Rank-1, Rank-5, rank-10, rank-15, and rank-20 is shown in Table 2 and is graphically shown in Fig. 4 and Fig. 5. From result attained it can be seen the proposed person re-identification model improves matching rate performance by 10.958%, 9.56%, 6.09%, 2.85%, 3.011% over existing person re-identification model [35] considering Rank-1, Rank-5, rank-10, rank-15, and rank-20, respectively. Similarly, the proposed person re-identification model improves matching rate performance by 12.996%, 5.32%, 3.102%, and 1.299% over existing person re-identification model [36] considering Rank-1, Rank-5, rank-10, and rank-20, respectively. Further, the proposed person re-identification model improves matching rate performance by 5.655%, 4.67%, 0.32%, 0.091% over existing person re-identification model [37] considering Rank-1, Rank-5, rank-10, and rank-20, respectively. Lastly, the proposed person re-identification model improves matching rate performance by 4.84%, 2.057%, 2.072%, and 2.31%, over existing person re-identification model [38] considering Rank-1, Rank-5, rank-10, and rank-20, respectively. From overall result attained it can be seen proposed person re-identification attain significant performance when compared with state-of-art person re-identification model.

Table 2: Matching rate performance evaluation for person re-identification by proposed model over state-of-art

Authors/Rank	**1**	**5**	**10**	**15**	**20**
W. Zhang et al., [36]	64	87	94	-	98
De cheng et al., [35]	65.5	83.1	91.1	95	96.3
L. Wu et al., [37]	69.4	87.6	96.7	-	99.2
McLaughlin et al., [38]	70	90	95	-	97
Our approach	**73.56**	**91.89**	**97.01**	**97.79**	**99.29**

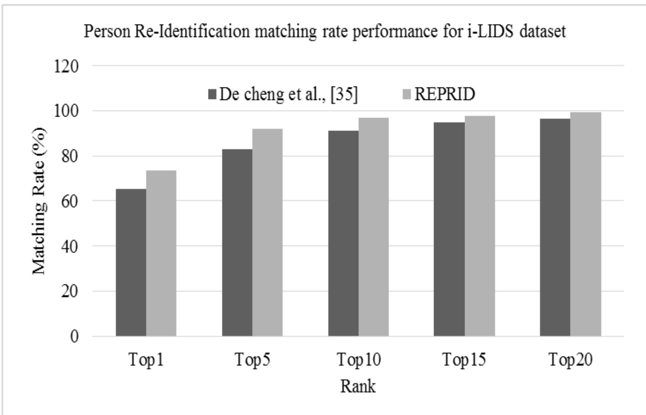

Fig. 3. Matching rate performance evaluation for person re-identification.

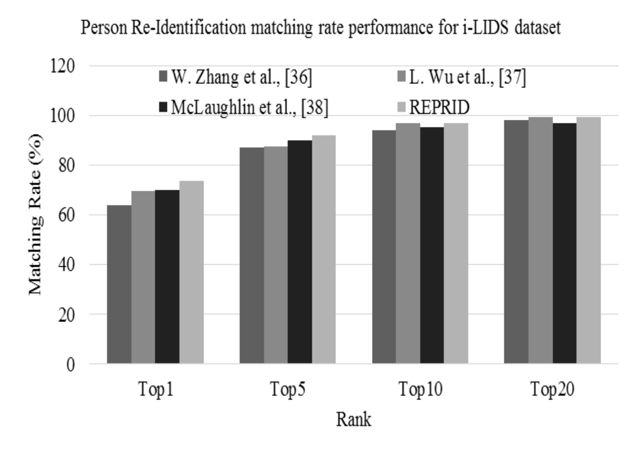

Fig. 4. Matching rate performance evaluation for person re-identification.

V. CONCLUSION

This work presented a robust learning and re-ranking method for person re-identification. The proposed KNN graph based learning model aid in improving ranking task. Further, the re-ranking optimizes the PRID outcome considering multiple person simultaneous appearances. Along with, our model can exploit the ranking outcome of state-of-art supervised based PRID techniques. Experiments are conducted on two standard benchmark. The proposed PRID model attains better matching rate performance when compared with various state-of-art techniques. The result attained shows the proposed PRID model is scalable and efficient when compared with existing PRID model.

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