American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-7, Issue-7, pp-210-218
www.ajer.org
Research Paper Open Access

A Study of Person Re-Identification System

Salwa Baabou[1], François Bremond[2], Awatef Ben Fradj[3], Mohamed Amine Farah [3], Abdennaceur Kachouri[3]

[1](National Engineering School of Gabes, University of Gabes, 6029 Gabes, Tunisia)
[2](INRIA Sophia Antipolis-Mediterranee, 2004 Route des Lucioles-BP93 06902 Sophia Antipolis, France)
[3](Laboratory of Electronics and Information Technology (LETI), National Engineering School of Sfax, University of Sfax, B.P.W.3038 Sfax, Tunisia)
Corresponding Author: Salwa Baabou

ABSTRACT: *Person Re-Identification (Re-ID) consists in recognizing an individual who has already been observed over a network of non-overlapping camera views (hence the term Re-Identification). However, the matching is challenging due to similarities of person's appearance across different cameras. Recent advances have shown that metric learning methods are effective for person Re-ID as they provide a robust metric for measuring (dis)similarities among (un)matched image pairs. However, these methods suffer from the Small Sample Size (SSS) problem due to the limited number of labelled training samples. This paper provides an overview of the classical approaches in Re-ID which consist in exploiting the appearance cues such as color or texture of clothing. Then, we navigate to the metric learning-based methods which consist to establish the corresponding/matching using matching function (similarity metric or a ranking function) of appearance signatures. In this direction, we start our discussion with appearance-based methods based on hand-crafted feature and the metric learning-based approaches. The relevant Re-ID approaches are described in detail. We present also the concept of RGB-D based Re-ID and we summarize the most recently work utilizing color-depth sensors. The commonly used benchmark datasets for person Re-Identification are summarized and discussed. The performance of some state-of-the-art person Re-ID approaches on most used benchmark datasets is also compared and analyzed.*

KEYWORDS – *Person Re-Identification, appearance-based methods, metric learning-based methods, RGB-D–based methods, survey*

Date of Submission: 04-07-2018 Date of acceptance: 19-07-2018

I. INTRODUCTION

Recognizing persons in a video surveillance scene in the real world is attractive and is now showing an increasing interest. It requires the ability to track people across multiple cameras and person Re-Identification (Re-ID) is a fundamental aspect of multi-camera tracking. The task of person Re-ID consists in assigning the same identifier to all instances of a particular individual captured in a series of images or videos, even after the occurrence of significant gaps over time or space. Current Re-Identification techniques being utilized present many difficulties and shortcomings. For instance, they rely solely on the exploitation of visual cues such as color, texture, and the subject's shape. Despite the many advances in this field, Re-ID is still an open problem and this motivated us to provide this review and to search more towards re-identifying persons over camera network.

It is worth noting, that the Re-Identification system, as appearing in the relevant literature, turns out to be divided into two distinctive steps (see Fig.1): *i)* extracting distinctive visual features to represent the human appearance and *ii)* learn or discover an optimal metric [1, 2, 3] that can maximize the distance between samples from different classes whilst minimizing the distance between those belonging to the same class. Regarding the first research group, color and texture based features prove to be widely used [4, 5]. However, the color or texture representations appear to be highly sensitive to pose and illumination changes, likely to result in more intra-person variations (differences prevailing among the same person's relevant features) than inter-person variations (differences distinguishing different persons relating features). To maintain a reliable matching and for good performance, sorting condidate matches using a matching function (similarity metric or a ranking function) of appearance signatures should be invariant against illumination change, viewpoint... and discriminative given high inter person similarity. In this regard, Support Vector Machine (SVM) equipped with ranking [6] and transfer learning [7] strategies as well as many available distance metric learning methods have been discovered and applied to be highly effective in matching a particular. Table.1 lists the recent surveys that are related to Person Re-Identification (Re-ID).

It is in this context that the present paper can be set, with an organizational structure conceived as follows: the main challenges affecting the person Re-Identification process are depicted in section 2, while Section 3 reviews the major related work of appearance and distance metric-based methods dealing with person Re-ID. An overview of RGB-D based person Re-ID approaches are also described and reviewed. Section 4 highlights the commonly used benchmark datasets for person Re-ID as well as the major state-of-the-art methods achieved experimental results and performances as assessed via iLIDS, ViPeR, CAVIAR and 3DPeS datasets. We also cite some important open issues that may attract further attention on the field of Person Re-ID in section 5. Finally, section 6 depicts the paper's major concluding remarks and paves the way for prospective future works.

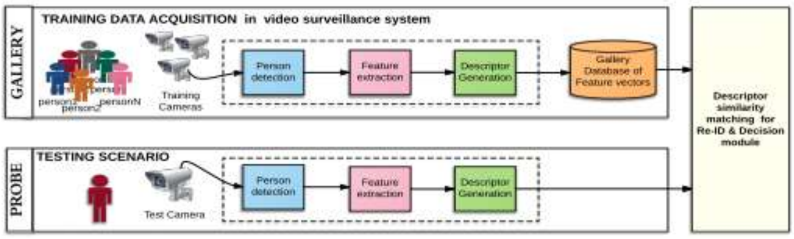

Figure 1: Person Re-ID diagram

Table 1 : Recent related surveys (most recent first)

Year	Paper
2016	Zheng et *al*. (2016)
2016	Jasher et *al*. (2016)
2014	Gala et *al*. (2014)
2014	Wang et *al*. (2014)
2014	Saghafi et *al*. (2014)
2013	Vezzani et *al*. (2013)

II. MAJOR PERSON RE-ID RELATED CHALLENGES

It is worth highlighting that Re-ID attached problem resides in the variation of a person's appearance across different cameras. A typical Re-ID system may have an image (single shot) or a video (multi-shot) as input for feature extraction and signature generation. Thus, the first step involved in Re-ID lies in learning a person's visual signature or model to establish a comparison among models to get either a match or a non match.

Extracting a reliable signature depends on the availability of good observations. Besides, faulty trajectory estimation and incorrect detections introduce errors in signature generation and extraction that may affect the Re-ID performance. The most obvious and simplest signature of a person is characterized by features like color, texture and shape. However, these features are hardly unique, not descriptive enough and prone to variations. Color/texture varies due to cross view illumination variations, pose variations, view angle or scale changes in multi-camera settings. For such a problem to be solved, the equalization among cameras seems highly imposed. Noteworthy also, is that different camera specific geometries greatly participate in rendering shape descriptors less discriminative. A subject may be fully or partially occluded by other subjects or items likely to result in errors predominating tracklets' match or combinations. Additionally, some person Re-ID body-part methods (such as SDALF, MPMC...) in a bid to solve the signature alignment issue but this problem still remains difficult to solve and the methods have nor proved to be effectively efficient as real detections and several annotations seem highly imposed. Worth citing, as well, is the low-image quality issue, as another problem prevalent in person Re-ID, where a subject's captured image may suffer from low resolution, noise or blur due to the limited imaging quality of surveillance cameras. All these issues affect the performance of person Re-ID which is still not robust enough to warrant high accuracy in practice.

III. OVERVIEW OF STATE-OF-THE-ART RE-ID METHODS

III. 1. Appearance-based Methods

The state-of-the-art descriptors have so far been reviewed in terms of the type of body model along with the kind of features applied to represent a person. In effect, each body part (or the whole image of the individual,

once no body part subdivision model has been used) is described using one or more different global, local or patch-based features. It is for this reason that appearance based methods appear to rely primarily on designing such descriptive characteristics as viewpoint invariance features [4], low-dimensional discriminative features [8] combined local and global features [9], multiple features' accumulation [10], bio-inspired features [11, 12] Fisher vector encoded features [13] and discriminative features by attributes [14]. Besides, color information has also been widely applied as a major person Re-Identification means. For an effective selection of the most descriptive person Re-ID features, [15] have applied to use Adaboost to draw the most effective representations from a set of local features. [10] have used a strategy based on localizing perceptual relevant human parts driven by asymmetry/symmetry principles to end up by proposing a special method named Symmetry Driven Accumulation of Local Features (SDALF), as a rather robust framework to background clutter. A Locally adaptive thresholding rule fit for the metric learning models (LADF) was introduced by [16], which has displayed a remarkably high performance in carrying out the person Re-ID involved tasks. Color Hexagonal-SIFT and Color Histogram Features (CHF) have been exhaustively exploited in [16] to devise a multi-camera handoff system suitably appropriate for person Re-ID purposes. [17] proposed a novel discriminative signature extracted from multiple local features and designed a signature distance measure by exploiting different body parts. [18] have proposed using reference descriptors rather than direct application of image features. A reference descriptor for a probe or gallery could be generated by computing the similarity scores contained between this probe or gallery and a reference set. This similarity-based representation has actually participated greatly in achieving the state-of-the-art performance on a widely applied dataset. In this regard, [19] have under taken to model the relevance prevailing among multiple image features through mutual information, while [13] have proposed an unsupervised approach to bottom-up feature importance mining on-the-fly specific to each probe image. In addition to appearance based features, [20] have also integrated gait biometric into the descriptor for person Re-ID purposes, enabling to handle color distortion and other appearance variations. As for [21], they have proposed a Local Maximal Occurrence (LOMO) feature, in which the horizontal occurrence of local features is used to achieve a stable representation to cater for the recurrent view changes. [22] proposed an hierarchical Gaussian descriptor for person Re-ID named GOG which consists of giving the feature representation of a person image and they adopt the part-based model. They assume that G regions of a person image are given in advance, which are typically horizontal stripes of the image. The proposed descriptor returns a feature vector of the regions. They explain the concept of GOG which consists of extracting from each region, local patches densely and describe each of these patches via a Gaussian distribution of pixel features named as patch Gaussians. Each of patch Gaussians is flattened and vectorized by considering the underlining geometry of Gaussians. Then, the patch Gaussians inside a region are summarized into a region Gaussian. They further flatten the region Gaussian and create a feature vector. Finally, the feature vectors extracted from all regions are concatenated into one vector. Most of appearance

methods based Re-ID present a representation model of the person appearance which should be discriminative enough to get better matching when applying the metric learning methods in order to increase the Re-ID performance.

To sum up, appearance based methods exploiting the low-level features; color/texture of the clothes; were not pertinent toward long term Re-ID applications where person's appearance change drastically as they are only suited for short-period Re-ID. In recent years, many works employing biometric information have been proposed especially in analysing the 3D body information which enables the view-point invariance for long term person Re-ID.

III. 2. Distance Metric Learning-based Methods

Several metric learning and matching schemes have been proposed as convenient alternatives for an effective process person re-identification to take place. These methods have been designed for the sake of learning the best metric between appearance features of the same person across camera pairs. These metric learning methods are categorized into: supervised versus unsupervised, global versus local ones. In Person Re-ID, most works fall into the scope of supervised global distance metric learning. Unsupervised methods mainly focus on feature design and feature extraction and they do not require manually labelling training samples, however, supervised methods generally require the assistance of manually labelled training samples which lead to better performance. Moreover, global metric learning methods focus on learning the vectors of the same class to be closer while pushing vectors of different classes further apart. [1] have proposed the Large-Margin Nearest Neighbor metric (LMNN), which belongs to the supervised local distance metric learning category, to help improving the traditional kNN classification made. However, using the k nearest within-class samples, LMNN has turned out to be a time-consuming process. As an LMNN variant, a slight improvement into the previously

reached results through incorporation of reject option for unfamiliar matches called LMNN-R has been introduced. To avoid the overfitting problems encountered in LMNN, Information Theoretic Metric Learning (ITML) [23] and Logistic Discriminant Metric Learning (LDML) [24] have also been applied as process improvement means. Conceived as an easy and efficiently strategy straight forward, called Keep It Simple and Straightforward Metric (KISSME), [4] envisaged learning a distance metric from equivalence constraints.
In respect to several other methods LMNN [25], ITML [23], LDML [24], KISSME does not rely on complex optimization and computationally expensive iterations. Nonetheless, applied on a real situation, the machine learning model's performance sounds likely to deteriorate over time as the newly incoming data appear to be liable to deviation from the initial training data. Traditional methods, which are time-consuming, are retrained in the batch mode as simultaneously applying as well as existing and new data. To cater for such a shortcoming, some well-known incremental learning algorithms, such as Self-Organizing Map and Growing Neural Gas[26], have been designed on the basis of neural network as a representation of the unlabeled data topological structure and a mean whereby data can be clustered into different classes.To be more appropriately fit for processing online data, [27] proposed an incremental learning method, called Self-Organizing Incremental Neural Network (SOINN) which noticeably outperforms the aforementioned algorithms by enabling to learn the necessary number of neural nodes and effectively representing the topological structure of input probability density. A prominent disadvantage of this method is that it uses Euclidean distance to measure the space separating the input data and nodes. However, given the prevalence intra-class and inter-class variations, the Mahalanobis metric sounds to berather suitably fit for coping with the person Re-ID related problems.

Several metric learning methods relating to person reidentification have also been advanced, such as Relative Distance Comparison (RDC) [28], Pair-wise Constrained Component Analysis (PCCA) and Local Fisher Discriminant Analysis (LFDA) [29, 30, 31]. Despite the promising Re-ID performance they could provide these methods, they seem to exhibit a linearity limitation and prone to properly overfit for application, especially in large scale and high dimensional learning scenarios. Additionally, these methods have not proved to cater effectively for the small scale sample size (SSS) problem persistent in the person Re-ID process, i.e. the number of samples considered for each simple subject sounds far smaller than the feature dimension itself. Authors in [30] proposed an effective method termed Geometric Preserving Local Fisher Discriminant Analysis (GeoPLFDA) integrating the LFDA discriminative framework and the geometric preserving method helping to approximate the nearest neighbor graph applying local maniflod. Actually LFDA [29] provides discriminative information through discarding the differently labeled samples and joining together the similarly labeled ones. As for the geometric preserving projection, it serves to provide local manifold structure regarding the nonlinear data induced by graph topology. Taking advantage of the complementarity and joint performance provided by both frameworks is reckoned to help noticeably in achieving significant improvement over most of the state-of-the-art approaches. In effect, most of previously designed distance metrics have been learned and recognized through the elaborated off-line and supervised approaches. Yet, they have not proved, they are not practical enough to be used in real-world applications wherein frequently online data flow without any label notification. In this respect, [31]have proposed a novel Online Learning approach helping to deal with Incremental Distance Metric (OLIDM) by modifying the SOINN through application of the Mahalanobis distance metric to cluster incoming data into neural nodes. Such metric serves to maximize the likelihood of true image pair matches with a smaller distance than that of a wrong matched pair. A number of other elaborated works appear in the literature under taking to apply neural network models to address the problem of person Re-Identification. Worth citing is the set Label Model devised by [19] which applies the Neighborhood Component Analysis (NCA) and Deep Belief Network (DBN) on the features of the query and gallery image to improve Re-ID performance. [32] have managed to achieve a state-of-the-art performance by applying a deep neural network to learn pair-wise similarity. Aside from the methods that use Mahalanobis distance , some use other learning tools like Support Vector Machine(SVM) and boosting. As for [6], they have suggested formulating person re-identification as a ranking problem by training a primal RankSVM ranker in a bid to reach a linear function whereby to weigh the absolute difference persistent among samples. [15] proposed using the AdaBoost algorithm to select and combine many different kinds of simple features into a single similarity function.

III. 3. RGBD-based approaches for Person Re-ID

As the RGB appearance-based person Re-ID assume that persons wear the same clothes and exploit only 2D informations, a new concept based on depth is introduced [34, 35]; In comparison to RGB information, depth information can maintain more invariant even when suffering from clothing change and extreme illumination because it is independent of color and maintains more invariant for a longer period of time. In fact, extracting depth and skeleton information with depth cameras (e.g. Microsoft Kinect) is not difficult in an indoor environment.

Kinect sensors obtain depth value (distance to the camera) of each pixel by infrared, regardless of object color and illumination in indoor applications. With depth information, the life size point cloud and

skeleton of a person can be extracted providing shape and physical information of his/her body. Moreover, with depth value of each pixel, humans can be more easily segmented from background, so that background influence can
be largely eliminated. Only few works on depth-based person Re-ID have been proposed.
[34] exploited skeleton-based feature based on anthropometric measurement of distances between joints and geodesic distances on body surface. [36] built a point cloud model for each person as gallery by fusing a set of point clouds from different views and then applied Point Cloud Matching (PCM) to compute the distance between samples. [11] proposed depth voxel covariance descriptor and Eigen-depth feature to describe body shape.Eigen-depth feature is a covariance based feature and it is locally rotation invariant and does not require alignment of point clouds. The Eigen-depth feature can be viewed as a depth shape descriptor and thus can remove the ambiguity of using only anthropometric measurement of skeletons in the previous depth modeling for re-identification. Since RGB and depth information can be obtained simultaneously when using Kinect, some Re-ID methods have been developed to combine depth information and RGB appearance cues in order to extract more discriminative feature representation. These methods can be divided into two categories, the first type of method is appearance based methods which integrate appearance and depth information together. [36] proposed a Re-ID approach based on skeletal information. Feature descriptors are extracted around person skeletal joints and final person signature is obtained by concatenating these descriptors. The second type of method is based on geometric features: Re-ID is performed by matching body shapes in terms of whole point clouds warped to a standard pose with the described method. They adopt the anthropometric measure method for Re-ID. They use the 3D location of body joints provided by skeletal tracker to compute the geometric features, such as limb lengths and ratios. Moreover, [37] improved accuracy of clothing appearance descriptors by fusing them with anthropometric measures extracted from depth data. [38] presented a tri-modal method to combine RGB, depth and thermal features. [39] combined RGB-Height histogram and gait feature of depth information.

To sum up, with depth information the skeleton can be extracted providing physical information of the person's body and with the depth value of each pixel, humans can be easily segmented from background. Then, using depth information may overcome some challenges in RGB appearance-based methods such as illumination change, clothing change, color change and background clutter. However, despite the advantages of depth-based Re-ID comparing to RGB-based methods, limitations also come along with depth information. In fact, the depth images change significantly when a person's viewpoint changes and the noise from the devices exists which will affect seriously the use of depth information for person Re-Identification.

IV. BENCHMARK DATASETS AND EVALUATION METRICS

IV. 1. Main public Datasets available for Person Re-ID

Several benchmark datasets are actually used for person Re-ID and some commonly used ones are summarized in Table.2. The most tested benchmark dataset is ViPeR which contains 632 identities and two images for each identity. 10 random train/test splits are used for performance evaluation and each split has 316 different identities in both training and testing sets. Moreover, many of these datasets especially those of early days are relatively small in size but the recent ones are large such as Market-1501, Mars, DukeMTMC-reID and DukeMTMC4ReID.

Table 2: Summary of some widely used datasets for Person Re-ID [41]

Datasets	#ID	#Image	#Distractors	#Camera
ViPER	632	1,264	0	2
iLIDS	119	476	0	2
GRID	1025	1,275	775	8
CAVIAR	72	610	22	2
PRID2011	934	1,134	732	2
CUHK01	971	3,884	0	2
CUHK02	1,816	7,264	0	10 (5pairs)
CUHK03	1,467	13,164	0	10 (5pairs)
RAiD	43	1,264	0	4
PRID450S	450	900	0	2
Market-1501	1,501	32,668	0	6
ETHZ	148	148	0	1
3DPES	192	1,000	0	8
iLIDS-VID	300	600	0	2
MARS	1261	20,715	0	6
DukeMTMC-reID	1,812	36,441	408	8
DukeMTMC4ReID	1,852	46,261	439	8

Some recently elaborated RGB-D person Re-ID datasets. [40] have been able to capture depth information (3D body information) using depth sensors which are likely to be applied for evaluation purposes of depth-based features concerning Re-ID. Among the widely used RGB-D datasets (see Table.3, one could well cite: RGB-D person Re-Identification dataset, the BIWI RGBD-ID Dataset, the IAS-Lab RGBD-ID one, kinect REID, Vislab KS20 and RobotPKU RGBD-ID dataset…

-RGB-D Person Re-Identification Dataset [34]:
This dataset proposed by [34] is composed of 79 people related to four different groups (collaborative, walking1, walking2 and backwards) collected using Kinect v1 and the acquisitions were performed in different days with change in appearances (clothes).

-BIWI RGBD-ID Dataset [36]:
It consists of 50 persons (50 training and 56 testing video sequences at about 10fps) in front of a kinect v1, performing a certain motions(head movements and two walks towards the camera...).
This dataset contains RGB images, depth images, skeletal information and the ground plane coordinates.

-IAS-Lab RGBD-ID Dataset [42] :
It contains 11 different subjects (11 training and 22 testing sequences). These videos are acquired at about 30fps. For each person, three sequences were collected making rotations and walkings with different clothes and at different rooms.

-KinectREID Dataset [37] :
This dataset is mentioned in the gait based-Re-ID and contains 71 people with multiple frames of 483 walking video sequences(30fps).

-Vislab KS20 Dataset [43]:
This dataset is available for anthropometry based Re-ID and it contains 21 different subjects with 300 walking video sequences (30fps) for each subject acquired from kinect v2.

-RobotPKU RGBD-ID Dataset [44]:
It contains 180 video sequences (30fps) of 90 persons and for each subject the Still and Walking sequences were collected in different rooms.

Table 3: RGB-D datasets for Person Re-ID

Datasets	#subjects	#video
RGB-D Person Re-ID	79	316
BIWI RGBD-ID	50	50 (train)/56 (test)
IAS-LAB RGBD-ID	11	11 (train)/22 (test)
KinectRe-ID	71	483
Vislab KS20	20	300
RobotPKU RGBD-ID	90	180

IV.2. Evaluation Metrics

Cumulative Matching Characteristics (CMC) curve is usually used to evaluate Re-ID algorithms. This metric represents wherever each element in the gallery is ranked in terms of its comparison to the probe. Indeed, the probability for the correct match to be ranked either as equal to or lower than a particular value is plotted against the size of the gallery set. So basically, CMC is accurate as an evaluation method only when one ground truth for each query exists. However, when multiple ground truths exist in the gallery, the mean average precision ,is used for evaluation. The motivation is that a perfect Re-ID system should be able to return all true matches to the user. Therefore, mAP is used together with CMC for the Market-1501 dataset where multiple ground truths from multiple cameras exist for each query.

IV.3. Performance of some classical state-of-the-art Re-ID methods on benchmark datasets

The performance of some state-of-the-art methods on i-LIDS, ViPeR, CAVIAR and 3DPeS is reported in Table.4 where the rank 1 is set to 1.
Fig.4, Fig.5, Fig.6 and Fig.7 show the Re-ID accuracy of some state-of-the-art approaches (LMNN, ITML, KISSME, PCCA, LFDA, GeoPLFDA, LADF) on ViPeR, i-LIDS, CAVIAR and 3DPeS datasets for a gallery set size p=316, p=30, p=30, p=48, respectively.

Table 4: Rank-1 Matching rate (%) on the ViPeR, i-LIDS, CAVIAR and 3DPeS datasets

Methods	ViPER	i-LIDS	CAVIAR	3DPeS
LMNN	12.9	36.8	35.3	42.1
ITML	9.8	24.0	23.4	20.5
KISSME	21.2	39.1	43.1	43.2
PCCA	19.27	30.3	33.0	38.0
LFDA	24.18	40.6	40.8	47.1
GeoPLFDA	27.0	46.6	50.4	50.3
LADF	29.34	35.8	40.5	42.4

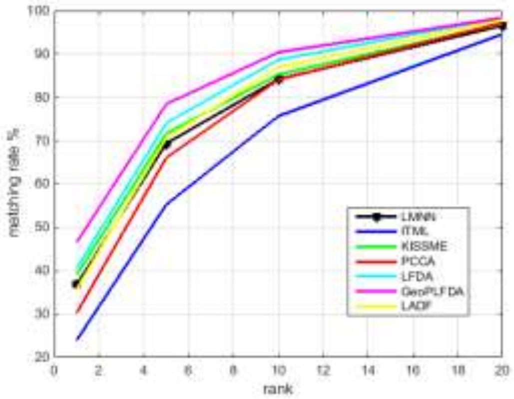

Figure 3: Re-ID accuracy (%) on i-LIDS dataset gallery set size p=30

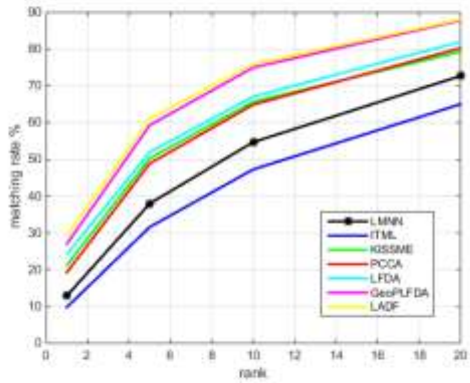

Figure 2: Re-ID accuracy (%) on ViPeR dataset for a for a gallery set size p=316

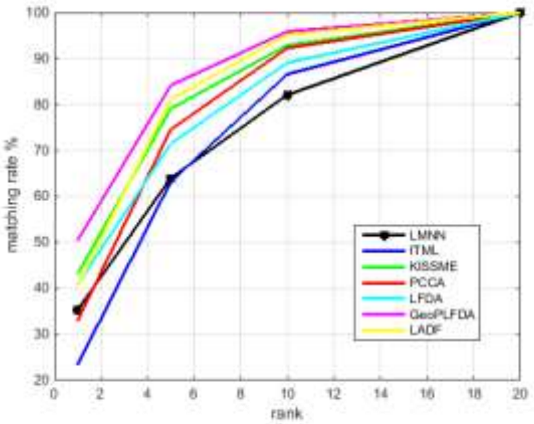

Figure 4: Re-ID accuracy (%) on CAVIAR dataset for a gallery set size p=30

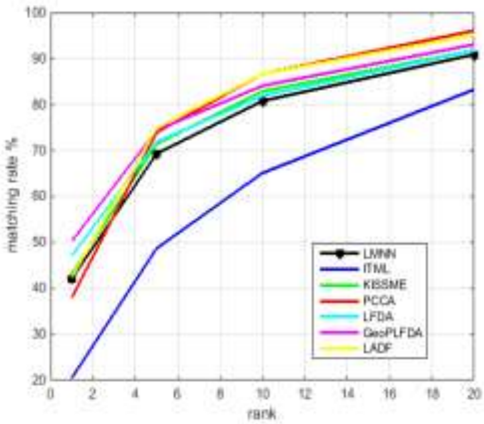

Figure 5: Re-ID accuracy (%) on 3DPeS dataset for a gallery set size p=48

V. OPEN ISSUES ON PERSON RE-ID

The problem of annotating large-scale datasets is still challenging in person Re-ID, as apart from drawing a bounding box for each subject, an ID has also to be assigned to the pedestrian and this task is not trivial as the person may re-enter the fields of view or enter another observation camera for a long time which make collaborative annotation difficult and explain why several datasets have a very limited number of images for each ID even if the last years witnessed a large-scale datasets such as Market-1501 and MARS but still far from satisfaction in real applications. Hence, the common similarity based ranking techniques do not scale well so that efficient matching schemes need to be explored. Besides, in order to maximize uniqueness, descriptors are often complex, high dimensional and expensive to extract. This also makes the recognition process compute intensive and complicated. These factors affect the temporal complexity of the system making real time performance difficult to achieve. Moreover, the open-world Re-ID problem is more challenging for two reasons: (*i*) the total number of unique people within each camera and the scene as a whole (cross-cameras) are both unknown, and *(ii*) each subject may appear in some unknown subset of the cameras. We can cite also in this context, the scale-adaptation problem in which the full body of the person is not appearing in the bounding box as well as the alignment problem where the person is not appearing in the center of the bounding boxes; these problems may affect the Re-ID accuracy and still among the open issues that we have to focus on it in the future to get better designed and more efficient Re-ID system.

In one word, despite the available works on person Re-Identification which solve some problems such as illumination and clothing change, background clutters and viewpoint variations...

Some other limitations still not resolved and challenging for person Re-ID and are considered as open issues for researchers.

VI. CONCLUSION

In this paper, we provide a comprehensive review of person Re-Identification which gained extensive interest in last years. First, we addressed the main challenges of person Re-ID. Then, the major existing methods for person Re-ID are reviewed which are appearance-based approaches and distance metric learning based methods. Departing from previous surveys, this paper gives more emphasis the concept of RGB-D using color-depth sensors (Kinect) which recently spread to person Re-Identification but still critical and need to be more studied in the future research. We also highlight some important open issues that may attract further attention for researchers. They include solving the problem of data volume issue, open-world Re-ID and depth-based Re-ID which may lead to a successful person Re-ID system in the future. To sum it up, as the person Re-ID process constitutes a rather challenging field, with vast opportunities for improvements and research perspectives, we hope that this paper would constitute a reference for anyone undertaking to elaborate on this interesting research field and present areas of future investigations.

REFERENCES

[1]. Weinberger, K.Q., Saul, L.K., Roweis, S., Distance metric learning for large margin nearest neighbor classification, in: Advances in Neural Information Processing Systems 18, MIT Press. pp. 1473–1480, 2006.

[2]. Dikmen, M., Akbas, E., Huang, T.S., Ahuja, N., Pedestrian recognition with a learned metric, in: Kimmel, R., Klette, R., Sugimoto, A. (Eds.), Computer Vision – ACCV 2010, Springer Berlin Heidelberg, Berlin, Heidelberg. pp. 501–512, 2011.

[3]. Pedagadi, S., Orwell, J., Velastin, S., Boghossian, B., 2013. Local fisher discriminant analysis for pedestrian re-identification.

[4]. Hirzer, M., Large scale metric learning from equivalence constraints, in: Proceedings of the 2012 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE Computer Society, Washington, DC, USA. pp. 2288–2295, 2012.

[5]. Kviatkovsky, I., Adam, A., Rivlin, E., . Color invariants for person reidentification. IEEE Transactions on Pattern Analysis and Machine Intelligence.

[6]. Prosser, B., Zheng, W.S., Gong, S., Xiang, T., Person re-identification by support vector ranking, in: Proceedings of the British Machine Vision Conference, BMVA Press. pp. 21.1–21.11, 2010..

[7]. Zheng,W.S., Gong, S., Xiang, T., Transfer re-identification: From person to set-based verification., in: CVPR, IEEE Computer Society. pp. 2650–2657, 2012.

[8]. Schwartz, W.R., Davis, L.S., Learning discriminative appearance-based models using partial least squares., in: SIBGRAPI, IEEE Computer Society. pp. 322–329 , 2009.

[9]. Bazzani, L., Cristani, M., Perina, A., Farenzena, M., Murino, V., Multiple-shot person re-identification by hpe signature, in: Proceedings of the 2010 20th International Conference on Pattern Recognition, IEEE Computer Society, Washington, DC, USA. pp. 1413–1416, 2010.

[10]. Farenzena, M., Bazzani, L., Perina, A., Murino, V., Cristani, M., Person re-identification by symmetry-driven accumulation of local features, In: IEEE Conf. Computer Vision and Pattern Recognition, pp. 2360–2367, 2010.

[11]. Ma, B., Su, Y., Jurie, F., Bicov: A novel image representation for person re-identification and face verification, 2012a .

[12]. Ma, B., Su, Y., Jurie, F., Local descriptors encoded by fisher vectors for person re-identification, in: Proceedings of the 12th International Conference on Computer Vision - Volume Part I, Springer-Verlag, Berlin, Heidelberg. pp. 413–422, 2012b.

[13]. Liu, C., Gong, S., Loy, C.C., On-the-fly feature importance mining for person re-identification. Pattern Recogn. 47, 1602–1615, 2014.

[14]. Pedagadi, S., Orwell, J., Velastin, S., Boghossian, B., Local fisher discriminant analysis for pedestrian re-identification, 2013

[15]. Gray, D., Tao, H., Viewpoint invariant pedestrian recognition with an ensemble of localized features, in: Forsyth, D., Torr, P., Zisserman, A. (Eds.), Computer Vision – ECCV 2008, Springer Berlin Heidelberg, Berlin, Heidelberg. pp. 262–275, 2008.

[16]. Li, Z., Chang, S., Liang, F., S. Huang, T., Cao, L., Smith, J., Learning locally-adaptive decision functions for person verification, 2013.

[17]. Martinel, N., Micheloni, C., Re-identify people in wide area camera network, 2012.

[18]. Bhanu, B., Kafai, M., Yang, S., Reference-based person re-identification. 2013 10th IEEE International Conference on Advanced Video and Signal Based Surveillance , 244–249, 2013.

[19]. Liu, H., Ma, B., Qin, L., Pang, J., Zhang, C., Huang, Q.,. Set-label modeling and deep metric learning on person re-identification. Neurocomputing 151, 1283 – 1292, 2015a.

[20]. Liu, Z., Zhang, Z.,Wu, Q.,Wang, Y., Enhancing person re-identification by integrating gait biometric. Neurocomputing 168, 1144 – 1156, 2015b.

[21]. Liao, S., Hu, Y., Zhu, X., Li, S., Person re-identification by local maximal occurrence representation and metric learning, 2015.

[22]. Matsukawa, T., Okabe, T., Suzuki, E., Sato, Y., Hierarchical gaussian descriptor for person re-identification, 2016.

[23]. Davis, J.V., Kulis, B., Jain, P., Sra, S., Dhillon, I.S., Information-theoretic metric learning, in: Proceedings of the 24th International Conference on Machine Learning, ACM, New York, NY, USA. pp. 209–216, 2007.

[24]. Guillaumin, M., Verbeek, J.J., Schmid, C., Is that you? metric learning approaches for face identification., in: ICCV, IEEE Computer Society. pp.498–505, 2009.

[25]. Weinberger, K.Q., Saul, L.K., Fast solvers and efficient implementations for distance metric learning, in: Proceedings of the 25th International Conference on Machine Learning, ACM, New York, NY, USA. pp. 1160–1167, 2008.

[26]. Sun, Y., Liu, H., Sun, Q., Online learning on incremental distance metric for person re-identification, 2014a..

[27]. Wu, L., Shen, C., van den Hengel, A., Deep recurrent convolutional networks for video-based person re-identification: An end-to-end approach. CoRR abs/1606.01609, 2016b.

[28]. Sugiyama, M., Local fisher discriminant analysis for supervised dimensionality reduction, in: Proceedings of the 23rd International Conference on Machine Learning, ACM, New York, NY, USA. pp. 905–912, 2006.

[29]. Sugiyama, M., Id´e, T., Nakajima, S., Sese, J., Semi-supervised local fisher discriminant analysis fordimensionality reduction. Machine Learning 78, 35, 2009.

[30]. Jia, J., Ruan, Q., Jin, Y., Geometric preserving local fisher discriminant analysis for person re-identification. Neurocomputing 205, 92 – 105, 2016.

[31]. Sun, Y., Liu, H., Sun, Q., Online learning on incremental distance metric for person re-identification, 2014b.

[32]. Yi, D., Lei, Z., Li, S.Z., Deep metric learning for practical person reidentification. CoRR abs/1407.4979, 2014a..

[33]. Li, W., Zhao, R., Xiao, T., Wang, X., Deepreid: Deep filter pairing neural network for person re-identification. 2014 IEEE Conference on Computer Vision and Pattern Recognition , 152–159, 2014b.

[34]. Barbosa, I. B., Cristani, M., Del Bue, A., Bazzani, L., & Murino, V., Re-identification with rgb-d sensors. In European Conference on Computer Vision (pp. 433-442). Springer, Berlin, Heidelberg, . 2012, October.

[35]. Saghafi, M.A., Hussain, A., Zaman, H.B., Saad, M.H.M., Review of person re-identification techniques. CoRR abs/1511.02319, 2015.

[36]. Munaro, M., Basso, A., Fossati, A., Gool, L.V., Menegatti, E., 3d reconstruction of freely moving persons for re-identification with a depth sensor. 2014 IEEE International Conference on Robotics and Automation (ICRA) , 4512–4519, 2014a.

[37]. Pala, F., Satta, R., Fumera, G., Roli, F., Multimodal person reidentification using rgb-d cameras 26, 1–1, 2015.

[38]. Mogelmose, A., Bahnsen, C., Moeslund, T., Clapes, A., Escalera, S., Tri-modal person re-identification with rgb, depth and thermal features, 2013.

[39]. John, V., Englebienne, G., Krose, B., Person re-identification using height-based gait in colour depth camera, 2013.

[40]. Cai, Z., Han, J., Liu, L., Shao, L., Rgb-d datasets using microsoft kinect or similar sensors: a survey. Multimedia Tools and Applications 76, 4313–4355, 2017.

[41]. M. Gou. Person re-identification datasets. http://robustsystems.coe.neu.edu/sites/robustsystems.coe.neu.edu/files/systems/projectpages/reiddataset.html, 2017.

[42]. Munaro, M., Ghidoni, S., Dizmen, D.T., Menegatti, E., A feature-based approach to people re-identification using skeleton keypoints. 2014 IEEE International Conference on Robotics and Automation (ICRA) , 5644–5651, 2014b.

[43]. Nambiar, A.M., Bernardino, A., Nascimento, J.C., Fred, A.L.N., Context-aware person re-identification in the wild via fusion of gait and anthropometric features. 2017 12th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2017) , 973–980, 2017.

[44]. Liu, H., Hu, L., Ma, L., Online rgb-d person re-identification based on metric model update. CAAI Transactions on Intelligence Technology 2, 48 – 55, 2017.

Salwa Baabou"A Study Of Person Re-Identification System."American Journal of Engineering Research (AJER), vol. 7, no. 07, 2018, pp. 210-218.