Scale-adaptive Low-resolution Person Re-identification

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Outline

- Research Background
- Motivation and Method
- Experiments and Analysis

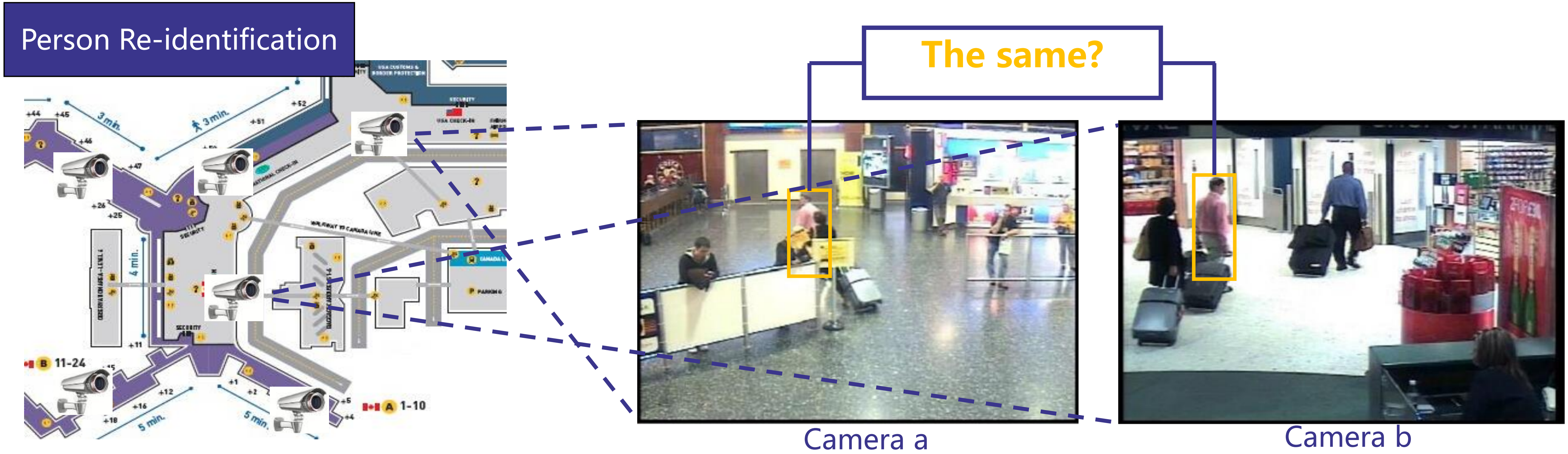
Research Background

大学共同利用機関法人 情報・システム研究機構
国立情報学研究所
National Institute of Informatics

Search for Zhou Kehua

1500 Investigators, one month

329 video clips



Research Background

Challenge

viewpoint variation

illumination change

scale zooming

intra distance
$D_{intra}(f(a_1), f(b_1)) = 0.3973$

$D_{intra} > D_{inter}$

inter distance
$D_{inter}(f(a_1), f(a_2)) = 0.1790$

Routine

Extract feature → **Measure distance** → **Re-rank**

Our Previous Research

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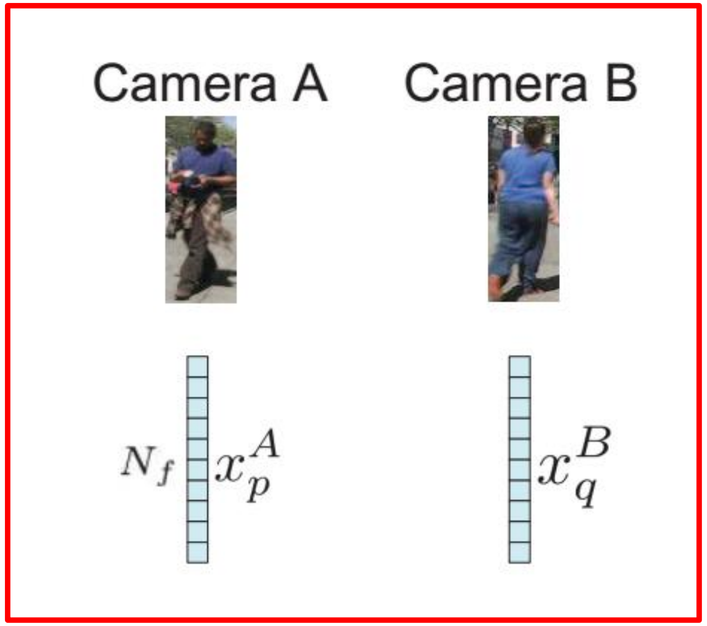
Extract feature

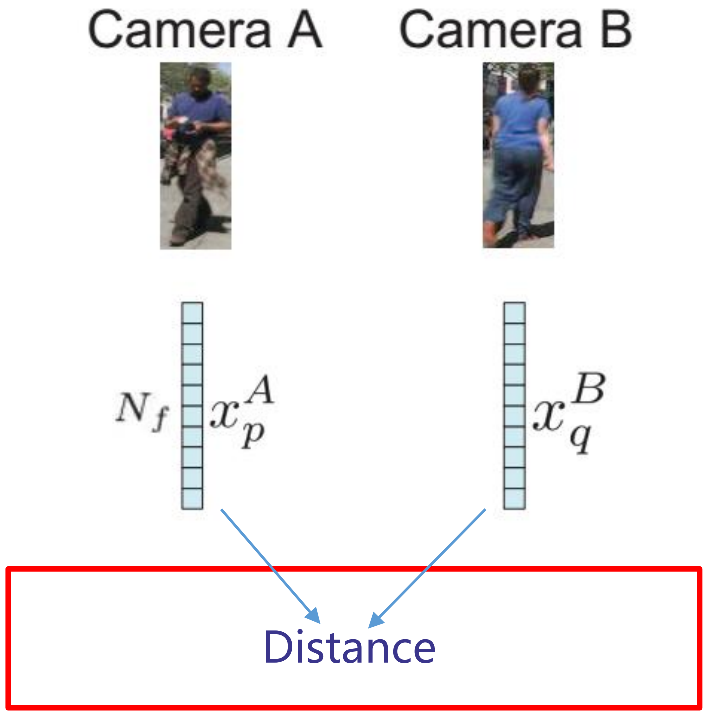
Construct discriminative visual descriptions that are robust and stable among different cameras.



- **IJCAI 2018:** Cascaded SR-GAN for Scale-Adaptive Low Resolution Person Re-identification
- **IJCAI 2016:** Scale-adaptive Low-resolution Person Re-identification via Learning A Discriminating Surface
- **TCYB 2017:** Person Reidentification via Discrepancy Matrix and Matrix Metric
- **ACM MM 2015 :** Multi-Level Fusion for Person Re-identification with Incomplete Marks
- **ICMR 2015:** Specific Person Retrieval via Incomplete Text Description

Measure distance

Utilize abundant training samples to learn a proper distance metric



- **ACM MM 2017:** Statistical Inference of Gaussian-Laplace Distribution for Person Verification
- **TMM 2016:** Zero-Shot Person Re-identification via Cross-View Consistency
- **ICASSP 2017:**TAICHI Distance for Person Re-identification
- **TCSVT 2017:** DeepList: Learning Deep Features with Adaptive Listwise Constraint for Person Re-identification

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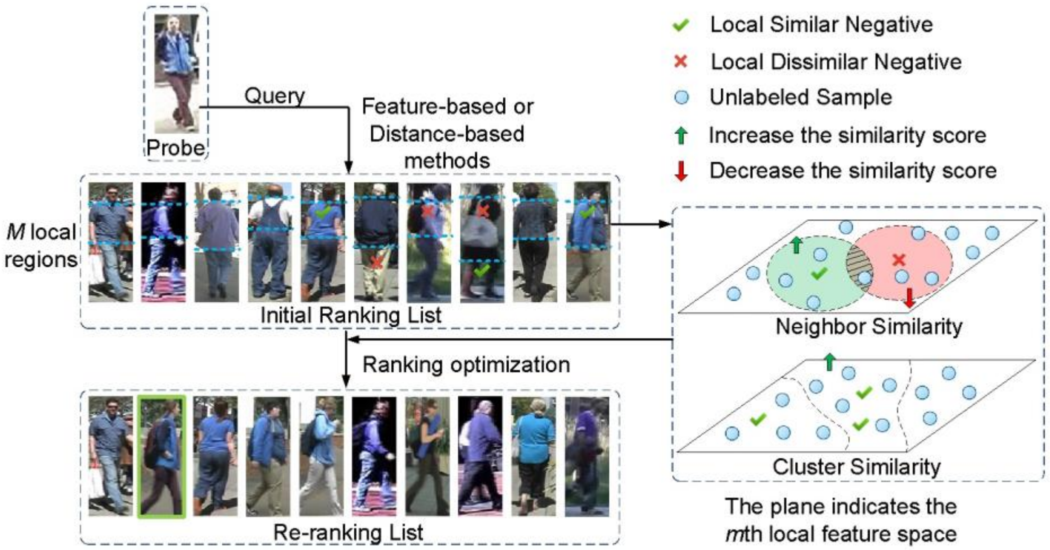
Re-rank

Re-rank the initial results automatically or with human feedback



Region-based Interactive Re-ranking

- **PCM 2014 :** Region-based Interactive Ranking Optimization For Person Re-identification (**Best paper award**)
- **ACM MM 2015:** Ranking Optimization for Person Re-identification via Similarity and Dissimilarity
- **TMM 2016**: Person Re-identification via Ranking Aggregation of Similarity Pulling and Dissimilarity Pushing

State-of-the-art

https://wangzwhu.github.io/home/re_id_resources.html

Re-id Resources

Re-id surveys

Person Re-identification Book, by Shaogang Gong
Person Re-identification: Past, Present and Future, by Liang Zheng
A Comprehensive Evaluation and Benchmark for Person Re-Identification: Features, Metrics, and Datasets, by Srikrishna Karanam
People Reidentification in Surveillance and Forensics: A survey, by Roberto Vezzani

Researchers

Affiliation	Person	Works
Queen Mary, University of London	Shaogang Gong	Attribute, Human-In-The-Loop, L1 Graph, Null Space, Unsupervised Transfer, Video Ranking, SVM
Sun Yat-sen University	Weishi Zheng	PRDC, Open-world RE-ID, Partial RE-ID, Low resolution RE-ID, Depth RE-ID, Cross-Scenario RE-ID, Top-push
Singapore University of Technology and Design	Liang Zheng	Market-1501, MARS, Query-Adaptive, K-reciprocal encoding, PRW, CamStyle, SPGAN, GAN, SVDNet
Graz University of Technology	Horst Bischof	KISSME, PRID 2011, PRID 450S, Relaxed Pairwise Metric
University of Udine	Niki Martinel	DCIA, Feature Warps, KEPLER
Institute of Automation, Chinese Academy of Sciences	Shengcai Liao	LOMO+XQDA, MLAPG
Amazon, Germany	Loris Bazzani	SDALF, CAVIAR4REID, PTZ, RGB-D, HPE
Chinese University of Hong Kong	Rui Zhao	SDC, DeepReid, Mid-level Filters, Salience Matching, Transferred Metric
Chinese University of Hong Kong	Chen Change Loy	Feature Importance, Manifold Ranking, POP, PETA, Color Naming
Chinese University of Hong Kong	Ying-Cong Chen	CRAFT, Mirror, CVDCA
Kyushu University	Tetsu Matsukawa	GOG, FTCNN, DALF
Hong Kong Baptist University	Andy Jinhua Ma	Domain Adaptation, QARR
Sun Yat-sen University	Liang Lin	JLSCR, Graph Matching, Deep Feature+RDC, End-to-End, DARI
Huazhong University of Science and Technology	Le An	Reference Descriptor, Common Space, Multi-hypergraph Fusion
Huazhong University of Science and Technology	Xiang Bai	Smoothed Manifold
Technion, Israel	Igor Kviatkovsky	Color Invariants
University of Maryland	Ejaz Ahmed	Improved Deep
Karlsruhe Institute of Technology	Martin Bauml	CAVIAR, Probabilistic, Semi-supervised
Institute of Automation, Chinese Academy of Sciences	Yang Yang	Deep Metric, MED_VL, Multi-Level Descriptors, LSSL, SCNCD
University of East Anglia	Ling Shao	Dense Invariant, Fast
Rensselaer Polytechnic Institute	Ziyan Wu	Real World, Pose Priors
Wuhan University	Xiaoyuan Jing	Intra-Inter-Video-Metric, Super-resolution
Northeastern University	Fei Xiong	Kernel-based Metric
University of Florence	Giuseppe Lisanti	ISR, MCK-CCA
Disney Research Pittsburgh	Slawomir Bak	One-Shot Metric, COSMATI
Xi'an Jiaotong University	DaPeng Chen	SLSC, EPKFM, Exampled-guided
Hong Kong Baptist University	Mang Ye	DGM, HCML, BDTR
Peking University	Shiliang Zhang	MSMT17, MTL-LORAE, PDC, DeepAttribute

Re-id Framework

1. Deep-person-reid implemented with PyTorch by Kaiyang Zhou.
2. Open-ReID implemented by Tong Xiao.
3. Person-reid-benchmark, implemented by Srikrishna Karanam.

AlignedReID: Surpassing Human-level Performance in Person Re-identification

Figure 6. Interface of our human performance evaluation system for CUHK03. The left side shows a query image and the right side shows 10 images sampled using our deep model.

Table 7. Results of human performance evaluation. We show the accuracies of the five annotators who did best in the evaluation. We also show our AlignedReID results with re-ranking.

	Market1501	CUHK03
Annotator Rank 1	**93.5**	**95.7**
Annotator Rank 2	91.1	91.9
Annotator Rank 3	90.6	91.2
Annotator Rank 4	90.0	91.1
Annotator Rank 5	88.3	90.0
AlignedReID (RK)	**94.0**	**96.1**

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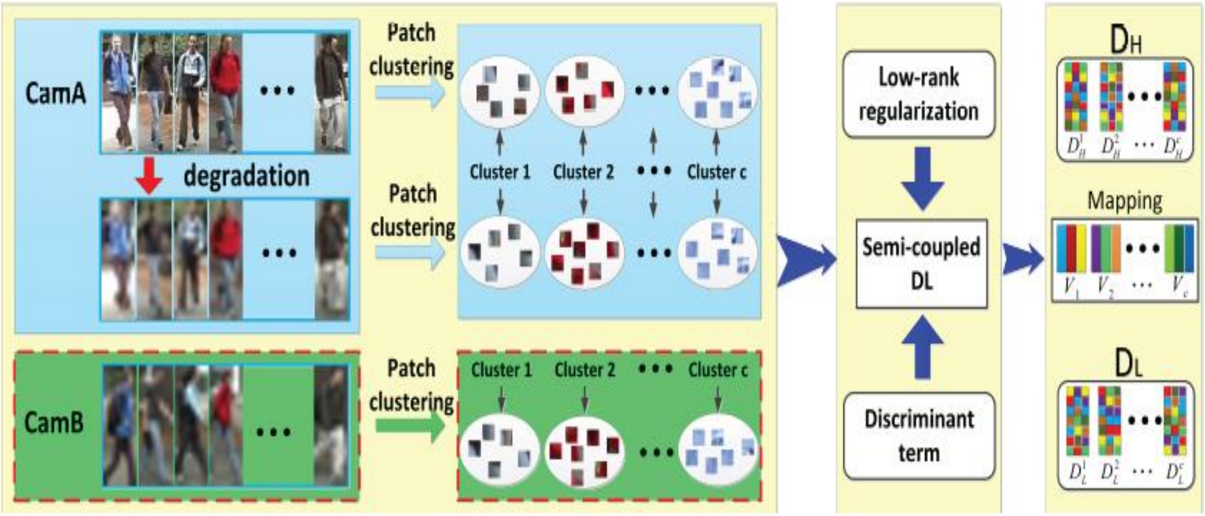
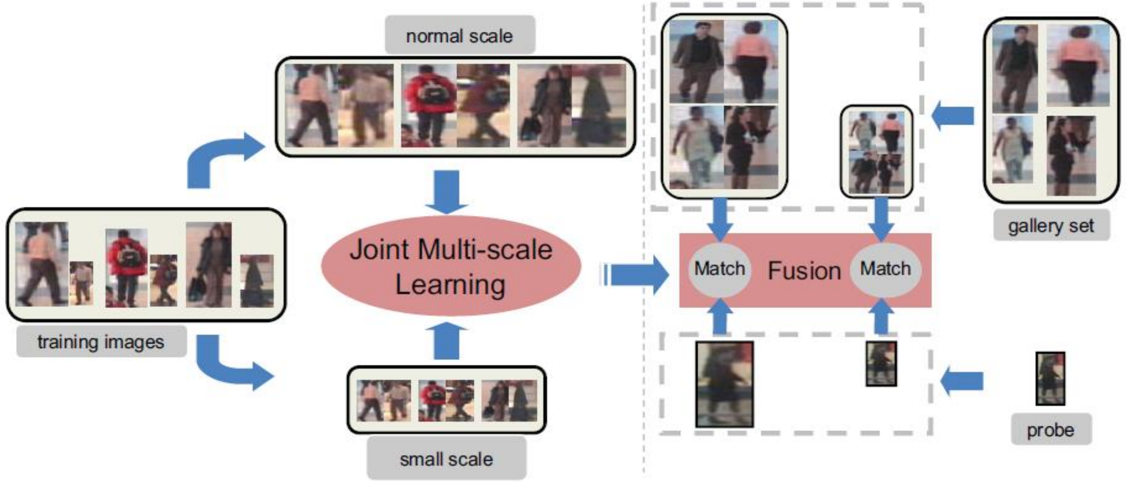
Low resolution Person Re-identification

[1]



[1] Xiao-Yuan Jing et al. Super-resolution person re-identification with semi-coupled low-rank discriminant dictionary learning. In CVPR, 2015.
[2] Xiang Li et al. Multi-scale learning for low-resolution person re-identification. In ICCV, 2015.

[2]



Based on the relatively ideal assumption that scales of LR are the same, the above two approaches show their effectiveness, through introducing relationship between HR and LR into traditional re-identification models.

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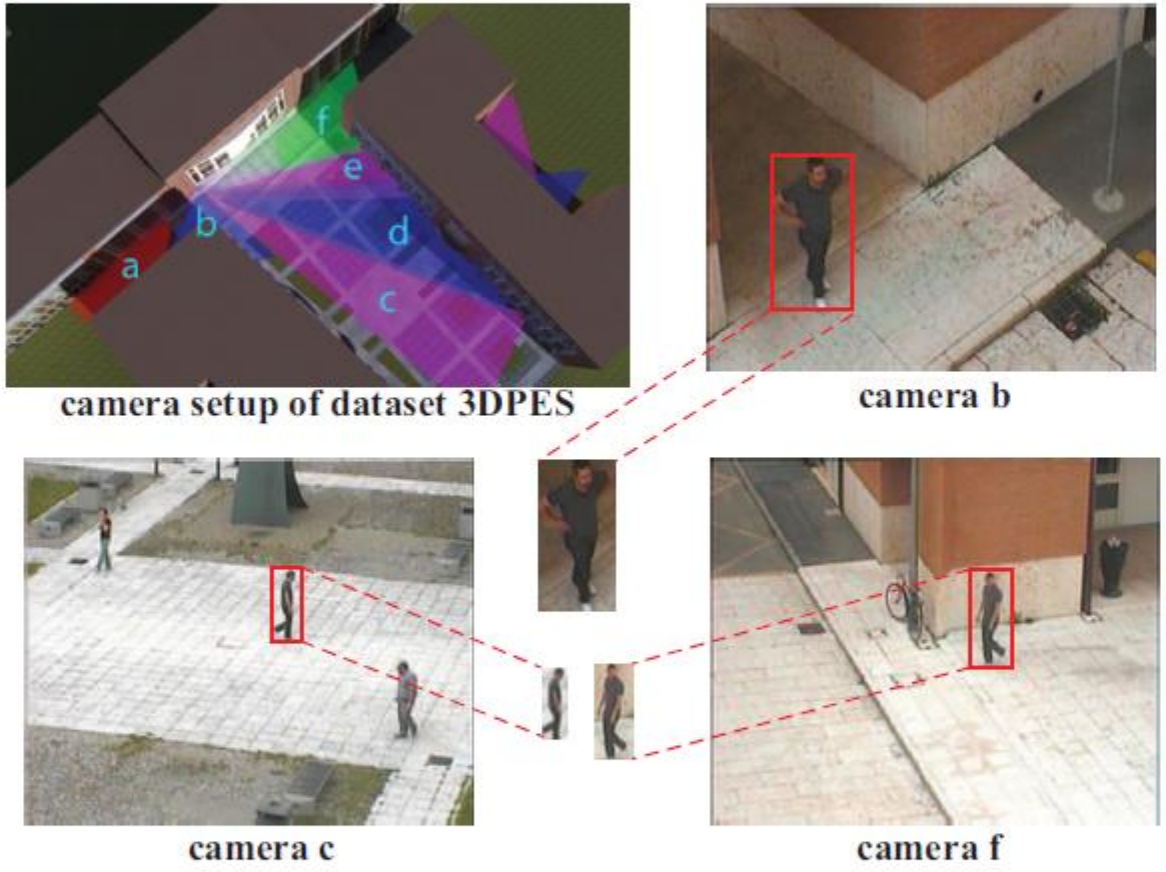
Scale-adaptive Low-resolution Person Re-identification



not only LR, but also holding different scales

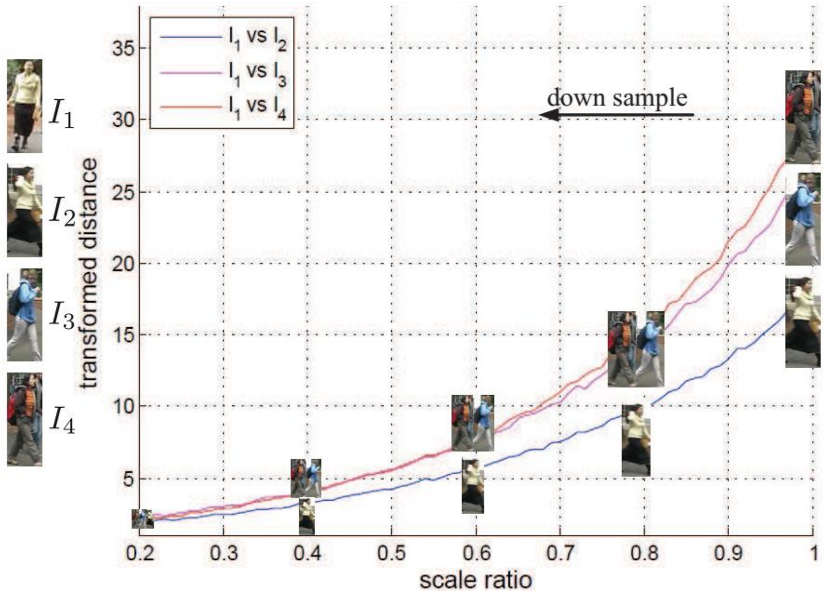
Given a LR probe image, the algorithm is expected to match against normal or even HR gallery images.

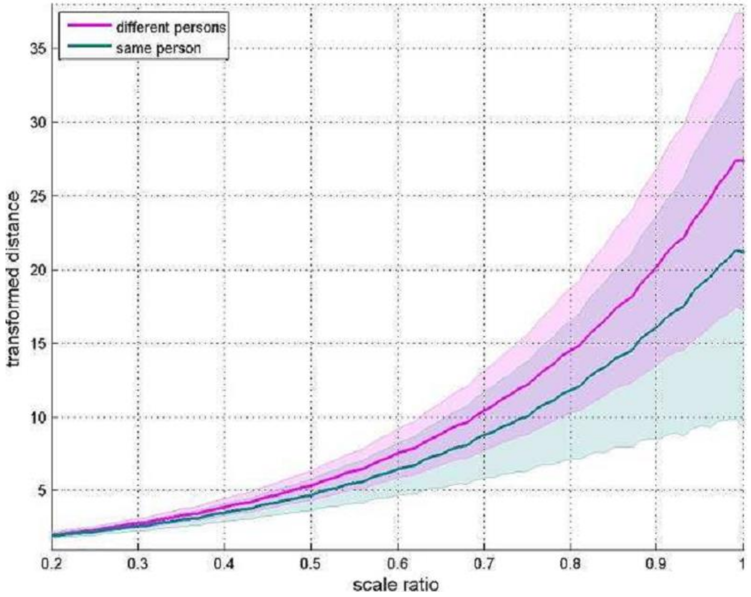
- In CVPR2015 , the probe images are uniformly 1/8 down-sampled from the original HR images.
- In ICCV2015, the resized scale is 1/4 of the original HR scale in common.

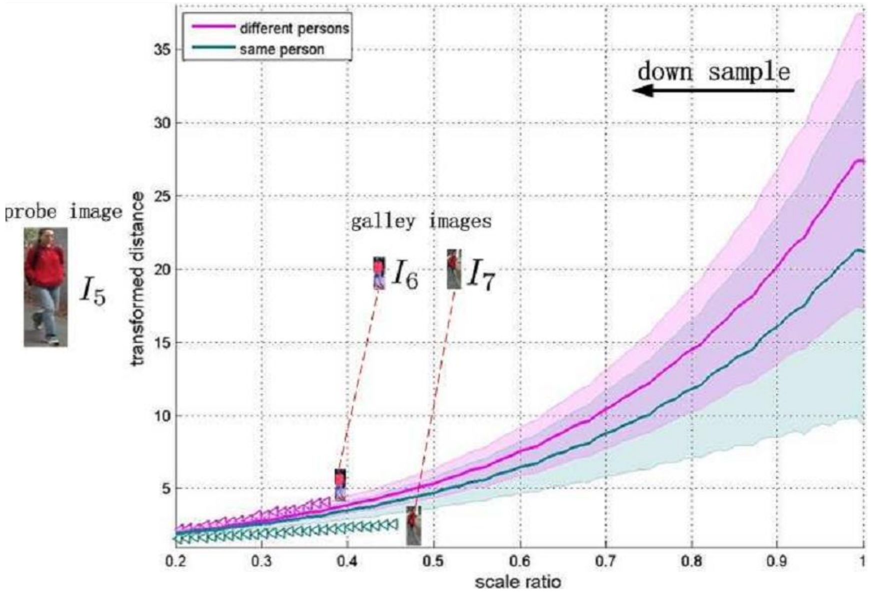
If there were 100 different scales in the dataset, the methods need to construct 100 different relationships, and it cannot be guaranteed that the 100 relationships work perfectly matching.

The practical task is that given a HR probe image, the algorithm is expected to match against LR gallery images with different scales.

Motivation 1







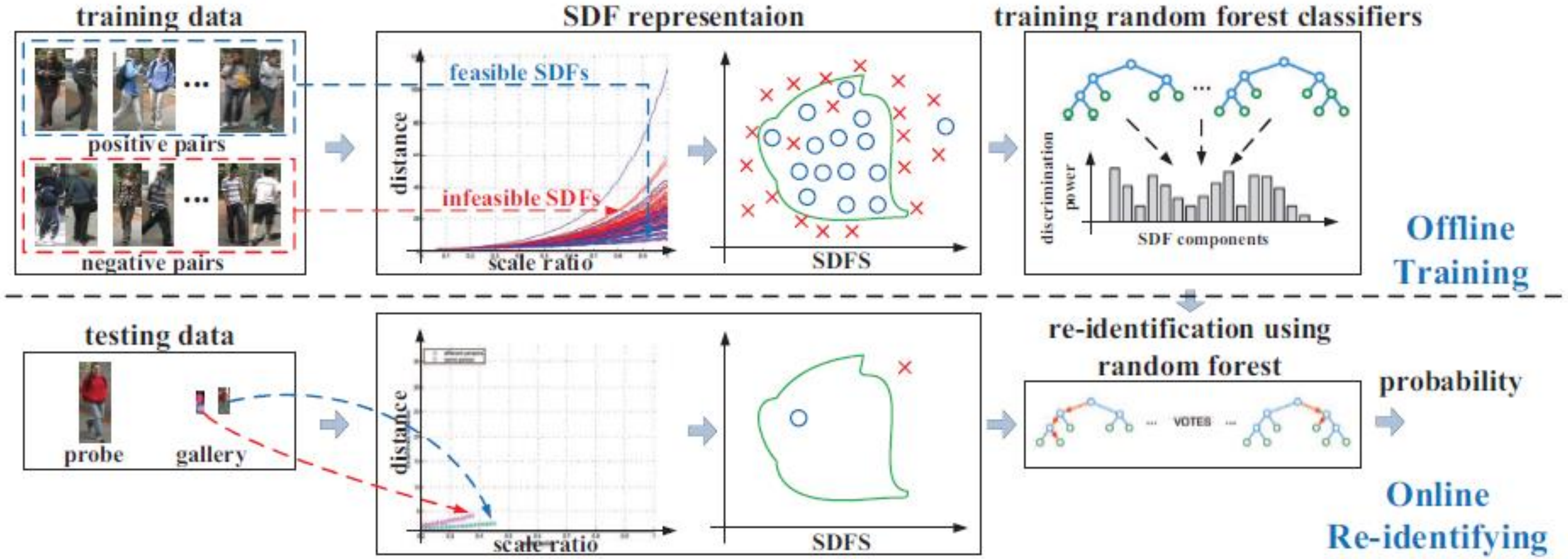
$$d' = exp(d * k)$$

scale-distance function

feasible and infeasible scale-distance functions, respectively for same persons and different persons, can be **discriminative** and used for re-identification.

learn a discriminating surface separating these two sets of functions in SDFS, and then classify a test function as feasible or infeasible.

Method 1 - SDF



$$\mathbf{x}_j^1, \mathbf{x}_j^{0.99}, \mathbf{x}_j^{0.98}, \ldots, \mathbf{x}_j^{0.06}, \mathbf{x}_j^{0.05}$$

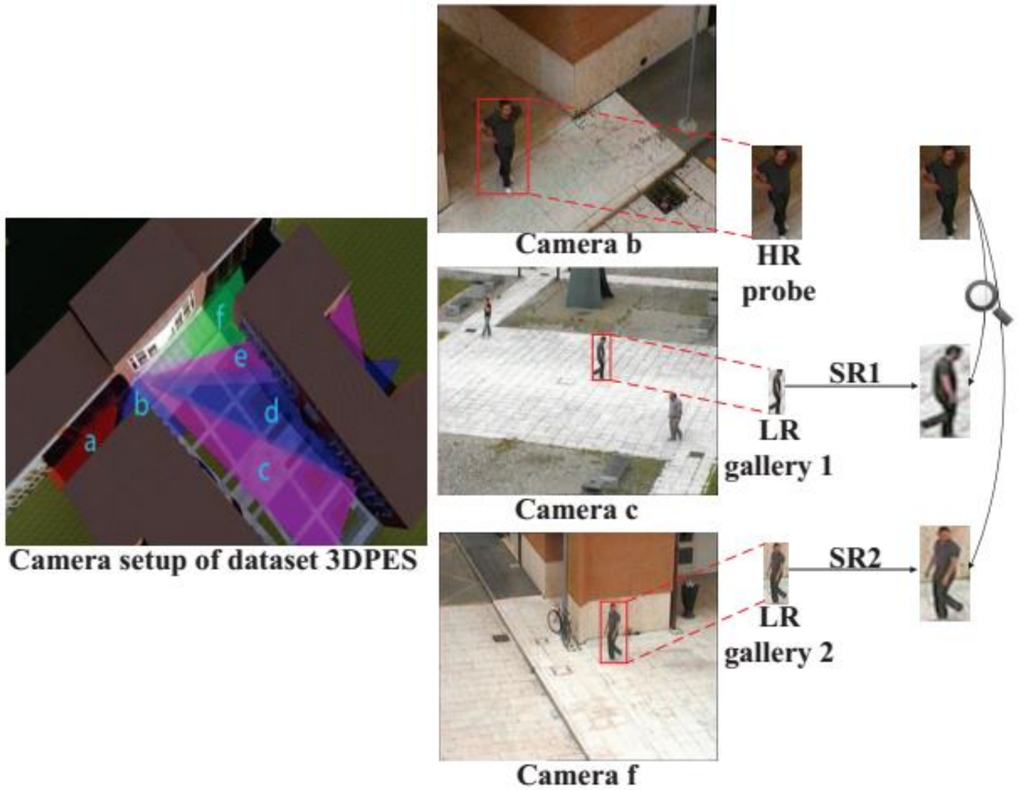
$$d_{i,j}(\mathbf{x}_i^1, \mathbf{x}_j^k), k \in [0.05, 1]$$

$$d'_{i,j}(\mathbf{x}_i^1, \mathbf{x}_j^k) = \exp(d_{i,j}(\mathbf{x}_i^1, \mathbf{x}_j^k) * k)$$

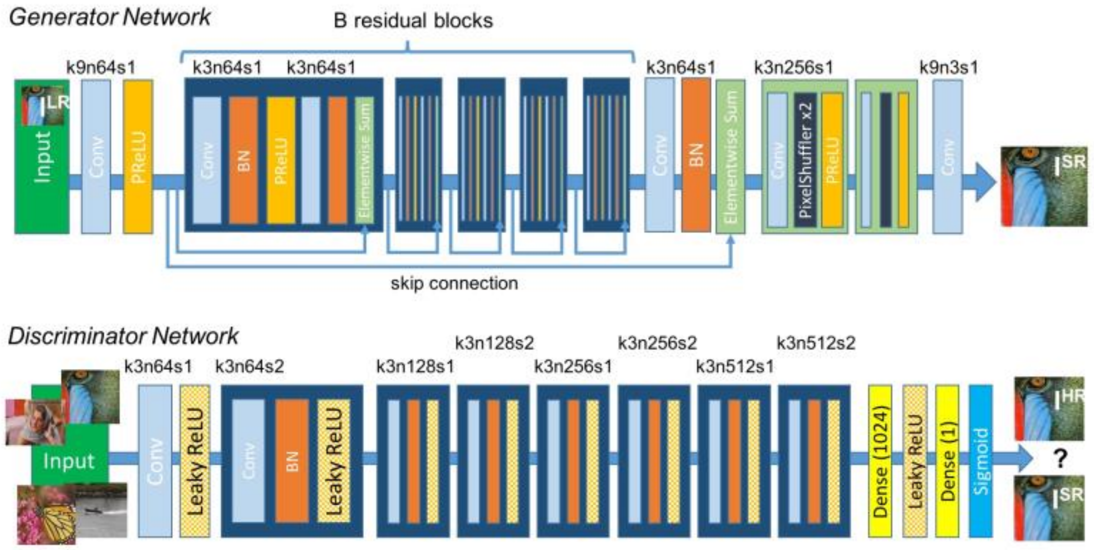
$$d'_{i,j}(k) = f(k, \mathbf{w}), k \in [0.05, 1]$$

$$\mathbf{w}_{i,j} = \underset{\mathbf{w}}{\operatorname{argmin}} \frac{1}{K} \sum_{k \in [0.05,1]} |d'_{i,j}(k) - f(k, \mathbf{w})|^2 + \lambda \sum_{n=0}^{N-1} |w_n|$$

Motivation 2



Super Resolution GAN



Pixel-wise **MSE loss**

Feature map **VGG loss**

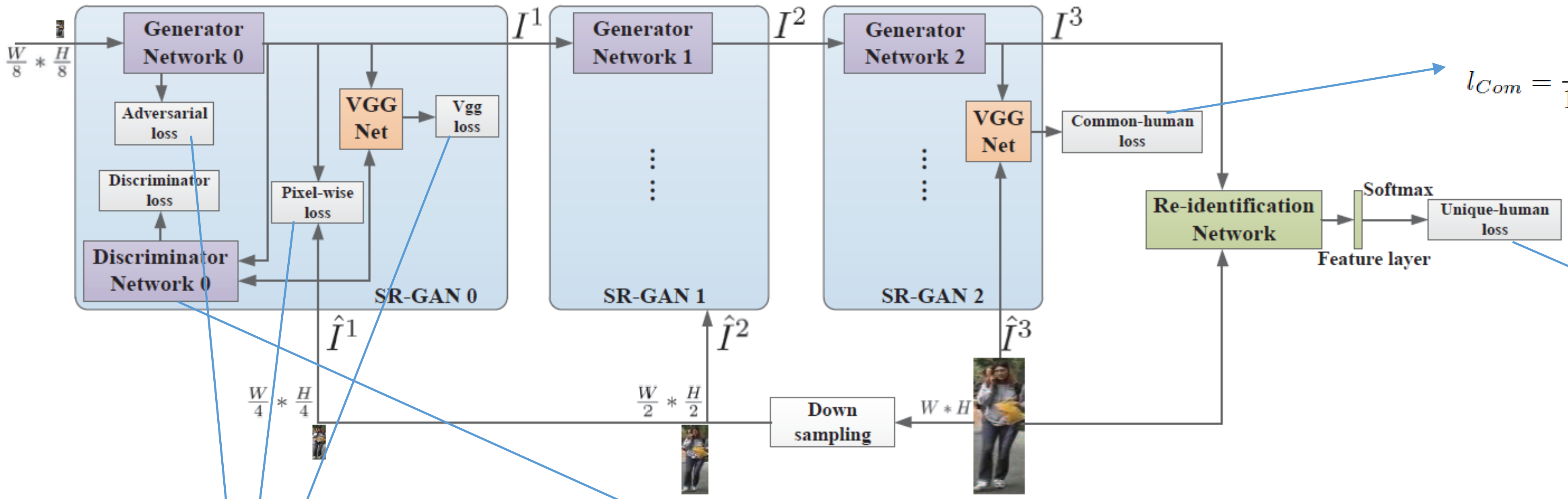
- **not for re-identification**

To promote the ability of discriminative person representation extracting, it requires plugging in the re-identification network, so that identity appearance information can be supplemented during SR.

- **fixed**

To promote the ability of scalable upscaling, it requires combining multiple SR-GANs, so that scalable LR images can be enlarged to a uniform HR.

Method 2 – CSR-GAN



$$l_{Com} = \frac{1}{1000}\sum_{c=1}^{1000}(\psi_c(\hat{I}^3) - \psi_c(I^3))^2$$

$$l_{Uni} = -\sum_{m=1}^{M} log(p(m))q(m)$$

$$l_{MSE}^{SR_k} = \frac{1}{r_{k+1}^2 WH}\sum_{x=1}^{r_{k+1}W}\sum_{y=1}^{r_{k+1}H}(\hat{I}^{k+1}_{x,y} - G_{\theta_{G_k}}(I^k)_{x,y})^2.$$

$$l_{Dis}^{SR} = -\sum_{k=0}^{2}\log D_{\theta_{D_k}}(\hat{I}^{k+1}) + \sum_{k=0}^{2}\log D_{\theta_{D_k}}(G_{\theta_{G_k}}(I^k))$$

$$l_{VGG}^{SR_k} = \frac{1}{W_{i,j}H_{i,j}}\sum_{x=1}^{W_{i,j}}\sum_{y=1}^{H_{i,j}}(\phi_{i,j}(\hat{I}^{k+1})_{x,y} - \phi_{i,j}(G_{\theta_{G_k}}(I^k))_{x,y})^2$$

$$l_{Adv}^{SR_k} = -\log D_{\theta_{D_k}}(G_{\theta_{G_k}}(I^k))$$

$$l_{Gen}^{SR} = \sum_{k=0}^{2} l_{MSE}^{SR_k} + \alpha\sum_{k=0}^{2} l_{VGG}^{SR_k} + \beta\sum_{k=0}^{2} l_{Adv}^{SR_k}$$

$$l_{total} = l_{Gen}^{SR} + l_{Dis}^{SR} + l_{Com} + l_{Uni}$$

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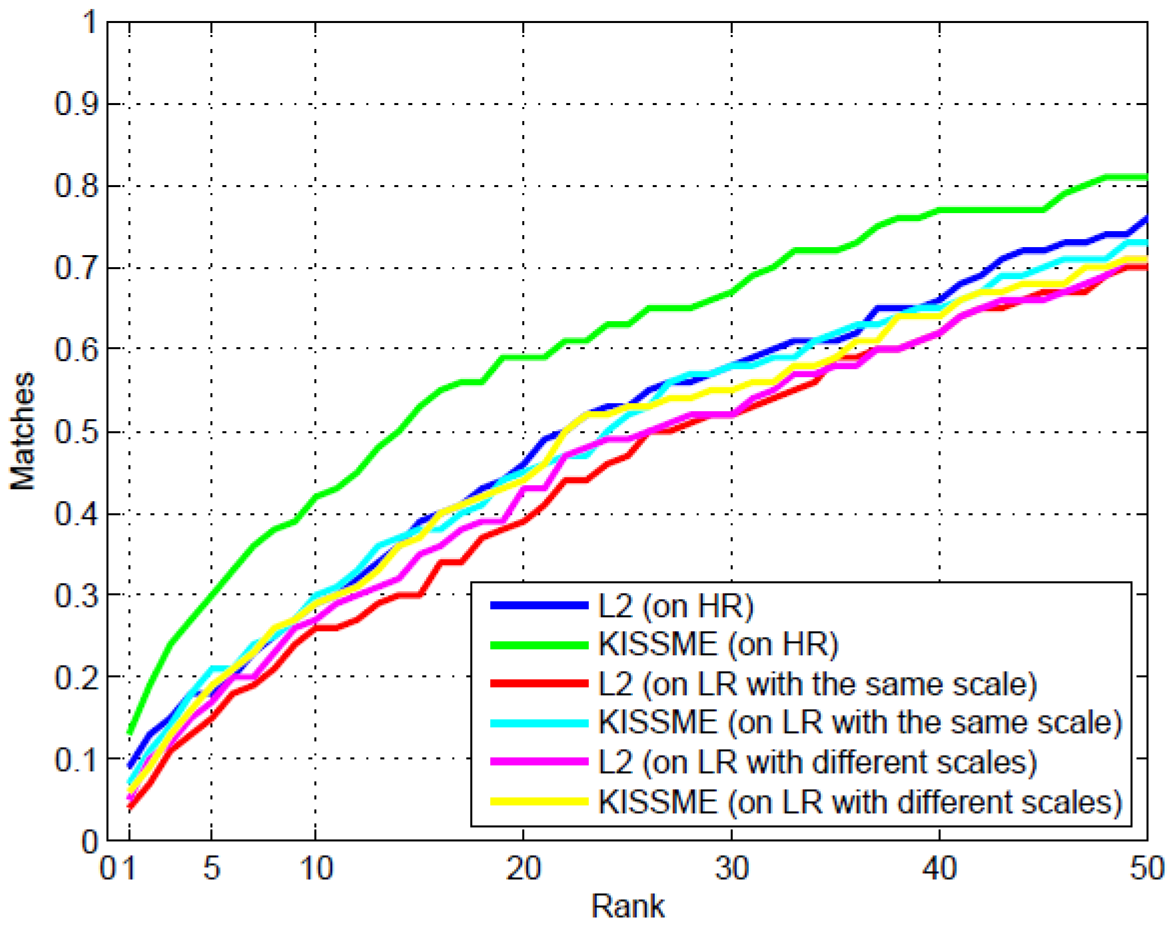
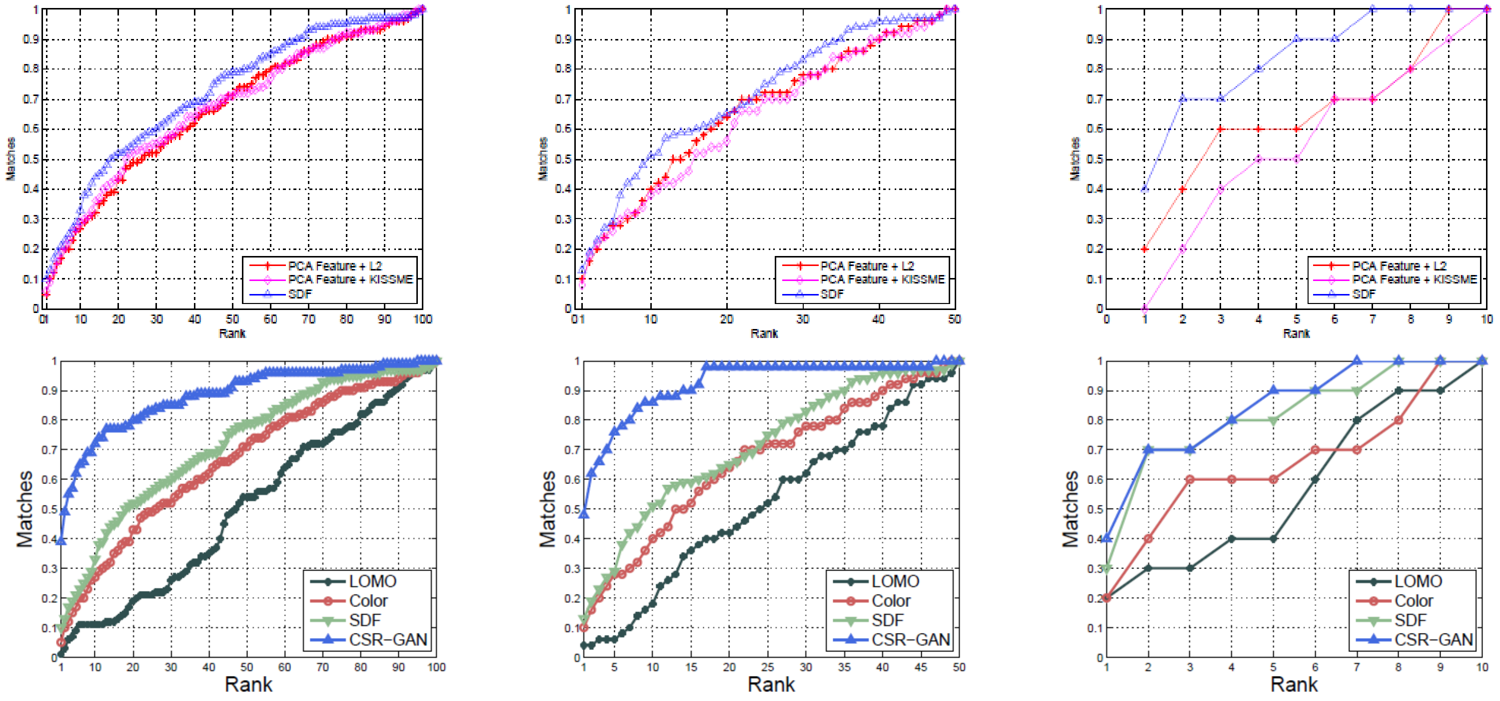
Experiments



The traditional feature distance model will gradually lose its effectiveness, as the resolution of images transforms from HR to LR with the same scale, then to LR with different scales.

Experiments

(a) SALR-VIPeR (b) SALR-PRID (c) CAVIAR



(a) SALR-VIPeR (b) SALR-PRID (c) CAVIAR

Evaluation on Scale-Adaptive SR

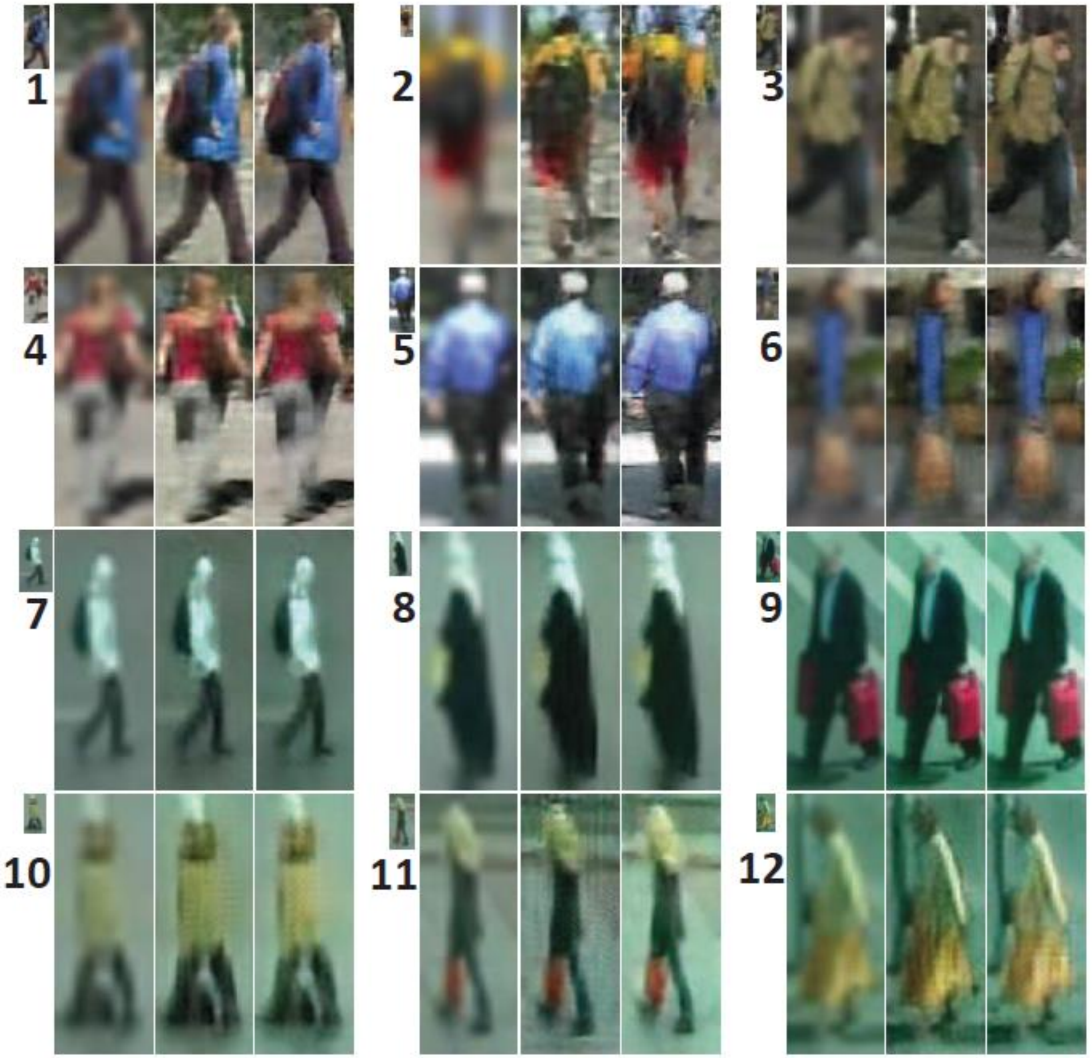


Table 1: The MOS test results on the testing images of three different datasets. We compared the proposed CSR-GAN method with the nearest and the bicubic methods.

Dataset	r	nearest	bicubic	CSR-GAN
SALR-VIPeR	$(0, \frac{1}{8}]$	1.05	1.12	**1.98**
	$(\frac{1}{8}, \frac{1}{4}]$	2.14	2.25	**3.78**
SALR-PRID	$(0, \frac{1}{8}]$	1.05	1.20	**2.05**
	$(\frac{1}{8}, \frac{1}{4}]$	2.30	2.55	**3.83**
CAVIAR	$(\frac{1}{4}, \frac{1}{2}]$	3.10	3.25	**4.20**

Comparison with State-of-the-art LR Methods

Table 2: Comparing with state-of-the-art LR person re-identification methods on MLR-VIPER. The $1^{st}/2^{nd}$ best results are indicated in red/blue.

	$rank@1$	$rank@5$	$rank@10$	$rank@20$
JUDEA	26.0	55.1	69.2	82.3
SLD^{2}L	20.3	44.0	62.0	78.2
SDF	9.52	38.1	52.4	68.0
SING	33.5	57.0	66.5	76.6
CSR-GAN	**37.2**	**62.3**	**71.6**	**83.7**

Conclusion

Raise a new issue

Propose two method

Thank You !