Unsupervised Posterior Probability Estimation for Score Fusion in Person Re-identification Systems

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What is Person Re-Identification?

Person Re-identification is the problem of identifying a person from an image, given a set of gallery images of different persons across different cameras or varying viewing angles. It has various potential applications in the areas of automated video surveillance and human computer interaction. However, he task of person re-identification poses considerable difficulties due to variations in illumination, viewpoint, pose and even occlusion.

Popular feature extraction approaches for person re-identification rely on:

- Color
- Texture
- Symmetry
- Visual Saliency

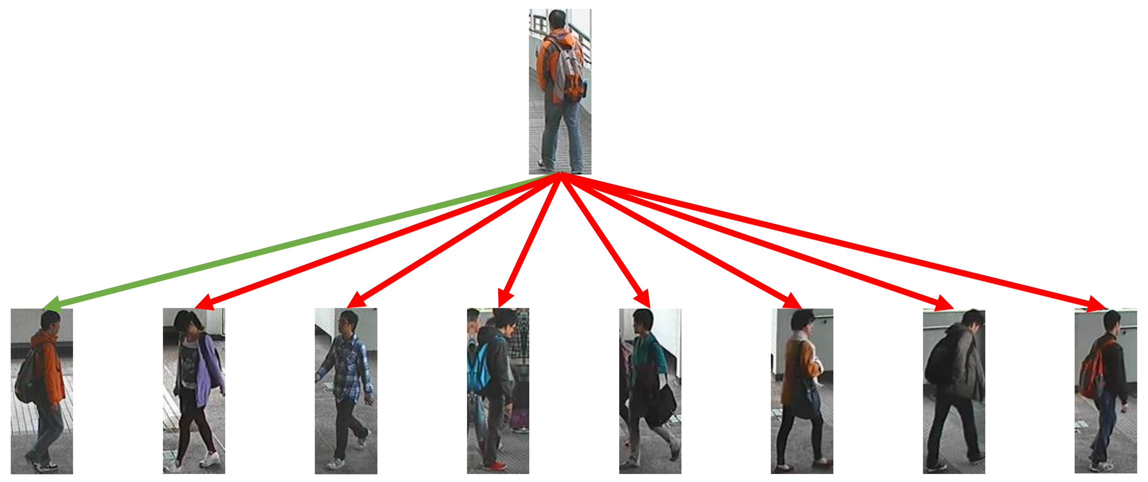

Fig. 1. The Person Re-Identification Problem

Motivation for Score Fusion in Person Re-Identification

- No common framework to combine different methods to exploit the different features
- Sharp decline in accuracy for all known methods with an increase in gallery size
- Benefits of score fusion for person re-identification is relatively unexplored compared to other recognition problems

Unsupervised Posterior Probability-based Score Fusion (UPPSF)

We propose a framework called Unsupervised Posterior Probability-based Score Fusion (UPPSF) for normalization and combination of scores obtained from matching of probe and gallery images using different methods.

Why use UPPSF?

- Vast improvement in performance over constituent algorithms
- Can deal with any score distribution
- Can combine scores of vastly different ranges

Estimation of Posterior Probabilities

- Each method for re-identification gives us score matrices of the form:

$$\mathbf{S}^k = \begin{bmatrix} s_{11}^k & s_{12}^k & \cdots & s_{1N}^k \\ s_{21}^k & s_{22}^k & \cdots & s_{2N}^k \\ \vdots & \vdots & \ddots & \vdots \\ s_{M1}^k & s_{M2}^k & \cdots & s_{MN}^k \end{bmatrix}$$

where $k = 1, 2, \dots, K$ are the different methods, M is the total number of probe images, and N is the total number of gallery images.

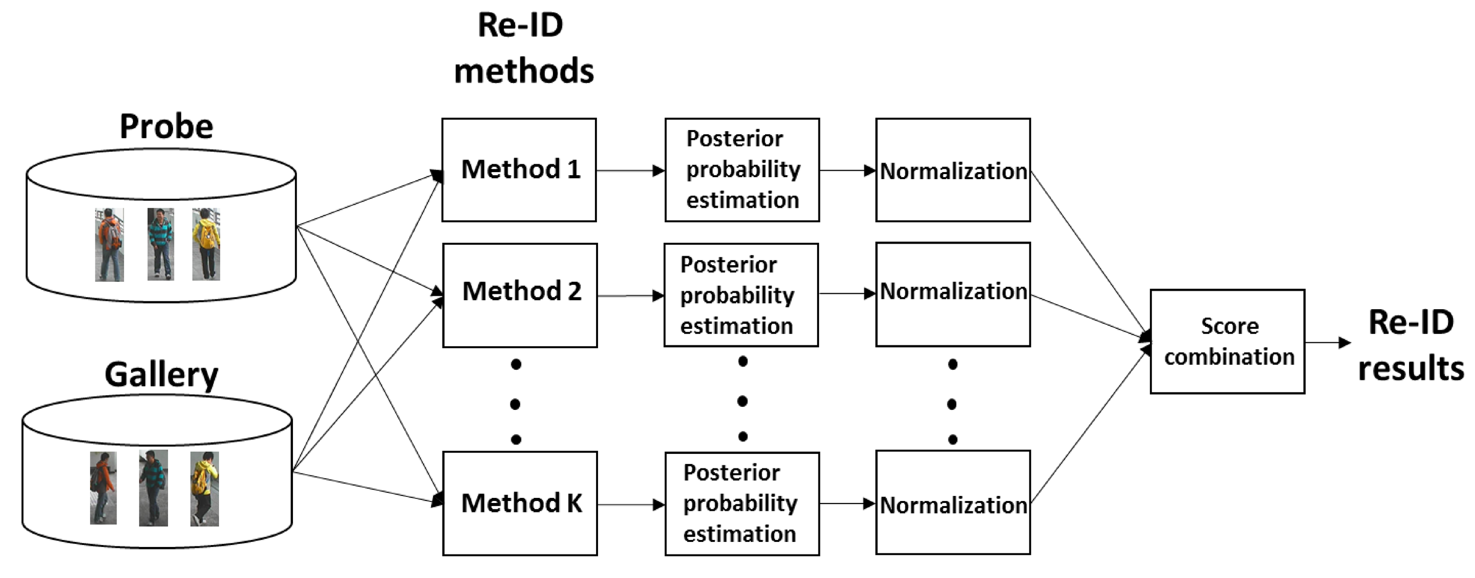

Fig. 2. Unsupervised Posterior Probability-based Score Fusion framework

- Estimate the posterior probabilities of a probe image having the same ID as each of the gallery images, i.e. $Pr(Y_m = n \mid \mathbf{S})$, where Y_m is the ID of the mth probe image, and $\mathbf{S}$ is the score matrix for a given method, for all gallery images, i.e., $n = 1, 2, \dots, N$.

- Log-linear model: We call this variant l-UPPSF. Here, Z is a normalizing constant.

$$\log Pr(Y_m = n \mid \mathbf{S}) = s_{mn} - \log Z$$

- Probit model: Here we use mean-shifted scores $\bar{s}_{mn}$. We call this variant p-UPPSF.

$$\mathbf{\Phi}^{-1}(Pr(Y_m = n \mid \mathbf{S}) \mid \sigma_m) = \bar{s}_{mn}$$

Normalization and Fusion

Estimated probabilities are normalized using tanh function on z-normalized posterior probability values. The values are mapped to the quasi-linear region of the tanh function, to normalize the range of posterior probability values for different methods.

$$f(p_{mn}) = \frac{1}{2}\left[\tanh\left(0.01\left(\frac{p_{mn} - \mu_m}{\sigma_m}\right)\right) + 1\right]$$

where $p_{mn} = Pr(Y_m = n \mid \mathbf{S})$, μ_m and σ_m are the mean and standard deviation of $\mathbf{p_m} = [p_{m1}, p_{m2}, \dots, p_{mN}]$.

Each score matrix is now added to get the fused score that is finally used for person re-identification.

$$\mathbf{S}_c = \sum_{k=1}^{K} \mathbf{S}^k$$

Results

- Score Fusion algorithm tested on VIPeR, CUHK01, CUHK03, ETHZ1 and ETHZ2 datasets
- Existing methods used: SDALF [1], SDC_knn [2], SDC_ocsvm [2], Midfilter [3] and f-FCH (color-based metric developed by us)
- Despite being unsupervised, the performance of our method is comparable to the only score fusion algorithm proposed for person re-identification: Query-Adaptive Fusion (supervised) [4]

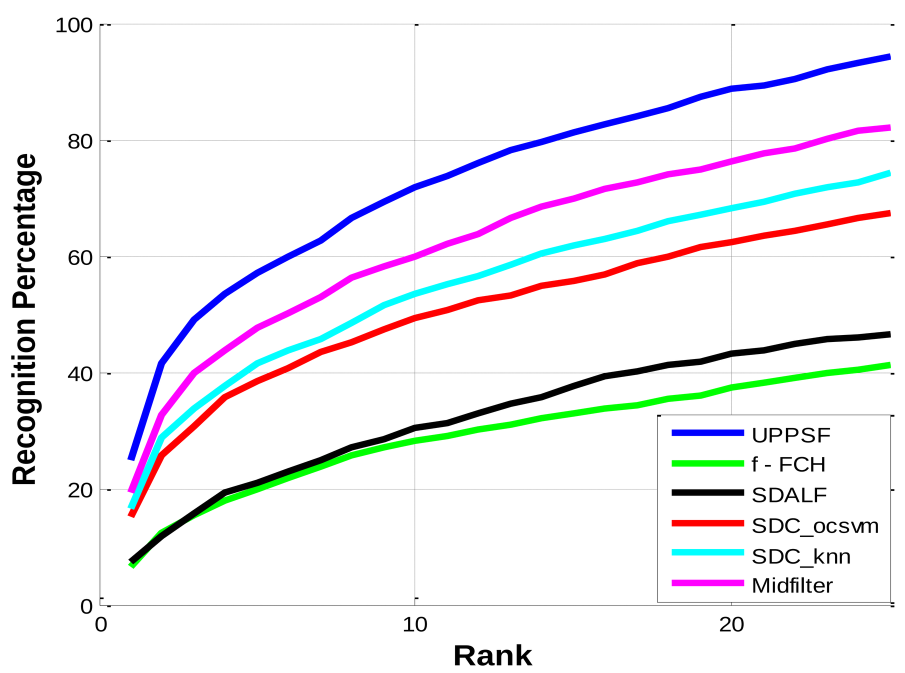

Fig. 4. Cumulative Matching Characteristics curve for CUHK01 dataset

Fig. 3. Person re-identification results with a sample probe image from CUHK01 dataset

Method	Rank-1	Rank-2	Rank-3	Rank-5	Rank-10	Rank-15	Rank-20
Color Histograms	22.86%	30.73%	35.71%	42.72%	53.91%	61.38%	65.98%
Color Names	21.74%	28.67%	33.96%	41.41%	50.24%	55.87%	60.85%
Local Binary Patterns	5.73%	9.46%	12.09%	15.52%	23.59%	29.26%	34.19%
Histogram of Oriented Gradients	5.40%	7.91%	9.73%	12.75%	19.42%	24.38%	28.20%
SDC_ocsvm	23.78%	32.82%	38.23%	45.70%	57.48%	65.46%	71.08%
Query-adaptive Fusion	**30.17%**	38.61%	43.82%	51.60%	62.44%	69.06%	73.81%
p-UPPSF	29.68%	38.91%	44.58%	52.76%	63.48%	70.27%	75.18%
l-UPPSF	30.00%	**39.40%**	**45.13%**	**53.35%**	**64.08%**	**71.23%**	**76.23%**

Table 1. Comparison of l-UPPSF and p-UPPSF with Query-adaptive fusion using the features in the first 5 rows

References

[1] M. Farenzena, L. Bazzani, A. Perina, V. Murino, and M. Cristani. Person re-identification by symmetry-driven accumulation of local features. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2010.

[2] R. Zhao, W. Ouyang, and X. Wang. Person re-identification by salience matching. In IEEE International Conference on Computer Vision (ICCV), 2013.

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[4] L. Zheng, S. Wang, L. Tian, F. He, Z. Liu, and Q. Tian. Query-Adaptive Late Fusion for Image Search and Person Re-identification. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015.